Personnel is Policy: Delegation and Political Misalignment in the Rulemaking Process*

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Abstract

We combine comprehensive data on the U.S. federal rulemaking process with individual-level personnel and voter registration records to study the consequences of partisan misalignment between regulators and the president. We present three main results. First, even important pieces of new regulation are frequently delegated to bureaucrats who are politically misaligned. Second, rules that are overseen by misaligned regulators take systematically longer to complete, are more verbose, generate more negative feedback from the public, and are more likely to be challenged in court. Third, in assigning regulators to rules, agency leaders often face a sharp tradeoff between political alignment and expertise. Agency frictions notwithstanding, they tend to resolve this tradeoff in favor of expertise.

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1 Introduction

Regulatory policy is a crucial tool through which governments around the world promote their political agendas, shaping trillions of dollars of economic activity every year (Coffrey et al., 2020; Crain and Crain, 2023; Trebbi et al., 2023). Rarely, if ever, however, do elected leaders craft specific pieces of regulation themselves. In modern administrative states like the U.S., the responsibility for drafting and implementing legally binding rules is typically delegated to small groups of bureaucrats with deep subject-matter expertise. These bureaucrats are tasked with developing regulations that are technically sound and advance the policy goals of their political superiors.

Anecdotal accounts suggest that bureaucrats' personal views may sometimes interfere with this mandate. For example, a high-ranking political appointee in the first Trump administration revealed in an (initially) anonymous op-ed in The New York Times that he and "many of the senior officials in [Trump's] own administration are working diligently from within to frustrate parts of his agenda."[1] On the other side of the aisle, entrenched bureaucrats reportedly stifled the Obama administration's attempts to overhaul the national security apparatus.[2] Examples like these and many others illustrate a canonical insight from economic theories of delegation: a principal can typically not achieve the first-best outcome unless her preferences align with those of the agent (see, e.g., Aghion and Tirole, 1997; Dessein, 2002; Alonso and Matouschek, 2008).

In this paper, we go beyond extant anecdotes and offer the first comprehensive empirical assessment of agency frictions due to ideological misalignment in the federal rulemaking process in the U.S. To this end, we combine comprehensive personnel records from the federal government with administrative voter registration lists and information on all rulemaking activity between the spring of 1997 and the fall of 2023. These data allow us to identify the specific individuals who were responsible for shepherding more than 35,000 different regulations through the federal rulemaking process. They also allow us to identify individual bureaucrats' partisan leanings. Drawing on this newly constructed data set, we test the idea that political misalignment among regulators distorts rulemaking.

Our analysis begins by establishing three stylized facts. First, we show that Democrats are over-represented among regulators, both relative to their share in the population as well as relative to their share among federal bureaucrats. Second, individual regulators are highly

[1] New York Times, "I Am Part of the Resistance Inside the Trump Administration", retrieved from https://www.nytimes.com/2018/09/05/opinion/trump-white-house-anonymous-resistance.html.

[2] Boston Globe, "Vote all you want. The secret government won't change," retrieved from https://www.bostonglobe.com/ideas/2014/10/18/vote-all-you-want-the-secret-government-won-change/jVSkXrENQlu8vNcBfMn9sL/story.html. See also Glennon (2015).

specialized. They tend to work on narrow issues and only on particular parts of the Code of Federal Regulations. Third, and contrary to the predictions of classic theories of delegation, agency heads and political appointees frequently assign important regulatory responsibilities to bureaucrats whose partisan preferences are not aligned with their own.

In the second part of the paper, we take the perspective of the principal and ask whether political misalignment is, in fact, associated with worse outcomes. Exploiting presidential transitions as a source of within-rule variation in the alignment of individual bureaucrats and their political superiors, we find that rules that are overseen by misaligned regulators take systematically longer to complete. We also find that the Office of Information and Regulatory Affairs (OIRA) engages in more drawn-out reviews when a rule is authored by misaligned regulators. OIRA is part of the Executive Office of the President. It reviews significant draft regulations to ensure that they align with the administration's policy priorities. Although almost all rules eventually clear OIRA review, the fact that this process takes longer when it involves misaligned regulators is suggestive of either greater suspicion on the part of OIRA, a higher frequency of (perceived) problems with the rule, or both.

Since slower rulemaking need not necessarily be counter to the interests of the principal, we turn to the notice-and-comment process and the actual text of enacted regulations as potentially quality-related outcomes. Leveraging state-of-the-art natural language processing tools, we classify more than 13 million comments as supporting or opposing a proposed rule. We show that rules that were initiated by politically aligned regulators are less likely to be opposed and more likely to be supported by interested parties. Drawing on tools from computational linguistics, we also show that the sections of the Code of Federal Regulations (CFR) that were authored or revised by misaligned regulators are more verbose and, therefore, more difficult to read. In this context, it is important to note that the Plain Writing Act of 2010 requires federal agencies to use clear, concise, and well-organized language, and that federal agencies use some of the same tools we do to assess the readability of proposed regulations. Taken together, these findings suggest that political misalignment is associated with lower-quality rulemaking.

To corroborate this interpretation, we directly address the possibility that greater textual complexity is indicative of higher precision and legal accuracy, in which case, misaligned regulators might produce rules that are actually better. With this objective in mind, we analyze court challenges to major rules, i.e., rules with an annual economic impact of $100 million or more. For each major rule, legal experts at the Institute for Policy Integrity coded whether that rule had been the subject of at least one federal lawsuit (Goodson et al., 2024). We find that rules that were authored by misaligned regulators are more likely to be challenged in court.

Overall, the analysis in the second part of the paper documents that misaligned regulators oversee rules that take longer to review and enact, are more verbose, generate more negative feedback from the public, and are more likely to be challenged in court. These findings provide empirical support for formal theories of delegation in which preference misalignment between principal and agent gives rise to agency frictions and suboptimal outcomes.

In light of these results, we ask in the third part of the paper, why do agency leaders delegate so frequently to misaligned bureaucrats? We provide a partial answer to this question by conducting a horse race between expertise and political alignment. For each potential candidate for assignment to a rule, we construct a measure of technical expertise in the specific subject areas that are covered by that rule. Using this measure, we show that subject-matter expertise matters *much* more than partisan alignment. In fact, our results imply that regulators' partisan leanings influence assignments only conditional on them being qualified.

The picture that emerges is that regulators are assigned to work on particular rules primarily based on their expertise. Since expertise in a given subject area tends to be concentrated in only a small number of individuals, agency heads and political appointees often need to choose between regulators who are either misaligned or lack the requisite expertise. To quantify this tradeoff, we rely on our measure of technical expertise at the regulator-rule level. We show that although 75% of rules in our data could have been assigned to at least one technical expert, only 57% had an available expert who was politically aligned. As a result, a principal that limits assignments to co-partisans would have needed to sacrifice expertise on nearly one in five rules. A back-of-the-envelope calculation suggests that the aggregate loss of expertise that such a principal would incur amounts to about 36% of the entire stock of expertise in the U.S. rulemaking process.

Broadly summarizing, our findings imply that agency frictions due to partisan misalignment among regulators come with a clear cost to their political principals. At the same time, given that technical expertise tends to be highly concentrated within federal agencies, attempts to increase the political alignment of rulemakers would result in a significant loss of expertise. For this reason alone, our results do *not* lend themselves to general statements about welfare. Moreover, even absent any explicit trade-off between partisanship and expertise, political frictions in rulemaking might be socially desirable in order to constrain the power of the executive. In this sense, the existence of a "deep state" may be good or bad.

Related Literature Our paper contributes to two strands of literature. First and foremost, we contribute to a large literature on the economics of regulation (e.g., Stigler, 1971; Bombardini et al., 2024; Trebbi et al., 2023; Gratton et al., 2021; Ash et al., 2025). While the study of the costs and benefits of regulation enjoys a long tradition within economics, the rulemaking process itself has received comparatively little attention. Our findings build on earlier efforts—primarily within political science and administrative law—to understand how ideological conflict shapes rulemaking within the U.S. system of separation of powers (see, e.g., Yackee, 2019, for a review). Potter (2017), for instance, shows that federal agencies can strategically delay rulemaking to avoid political oversight. Bolton et al. (2015) and Acs and Cameron (2013) find that ideological disagreement between agencies and the White House increases how long rules remain under OIRA review, and Doherty et al. (2019) find that turnover among career executives in key regulatory positions increases following turnover in the White House.[3]

We contribute to this literature by presenting the most extensive empirical analysis of rulemaking to date, both in terms of temporal coverage and the number of agencies, regulators, and rules studied. Our analysis of partisan conflict goes beyond traditional outcomes like duration and delay to explore the quality of regulatory text, public support through a comprehensive analysis of comments, and legal challenges in the courts. By examining canonical agency issues between politicians and bureaucrats, our study begins to open the black box of the regulatory process. To the best of our knowledge, we are the first to link individual regulators to voter registration records, providing novel evidence on the presence of agency frictions due to differences in political views.

Second, our paper contributes to an emerging literature on the role of ideology in shaping outcomes within organizations. Spenkuch et al. (2023) find that ideological alignment between bureaucrats and the White House is associated with lower cost overruns on federal procurement contracts. Focusing on the private sector, Colonnelli et al. (2022) show that Brazilian business owners are more likely to employ copartisans; Chinoy and Koenen (2024) present evidence of partisan workplace segregation in the U.S.; and Fos et al. (2022) document increasing polarization among top executives of publicly traded companies. In our analysis, we uncover a systematic relationship between the partisan leanings of individual bureaucrats and a broad range of important regulatory outcomes.

2 Data and Context

Our analysis combines data on the rulemaking activities of the U.S. federal government with personnel records from the Office of Personnel Management (OPM), and administrative voter registration lists. In this section, we describe the sources of these data, how we link them,

[3]Earlier, theoretical work tries to understand how Congress controls bureaucratic agencies (McCubbins et al., 1987; McCubbins and Schwartz, 1984; Moe, 1987), how legislators delegate authority to bureaucrats (Epstein and O'Halloran, 1994; Gailmard, 2009; Huber, 2002), and how bureaucrats can be incentivized to acquire expertise (Gailmard and Patty, 2013).

and how we use them to construct the key variables in our analysis. Additional details are provided in the Appendix.

2.1 A Primer on Federal Rulemaking

Federal departments and agencies issue and enforce legally binding regulations. The process for developing or changing regulations is governed by the Administrative Procedure Act (APA) of 1946, which requires agencies to draft proposals and invite comments before issuing final rules. Figure 1 illustrates the typical steps in this process. First, an agency identifies a need for regulation, prompted by statutory mandates, policy priorities, or emerging issues. It then drafts a Notice of Proposed Rulemaking (NPRM), which explains the proposed regulation. The NPRM is published in the Federal Register along with instructions for public comment. The commenting period typically lasts 30 to 90 days, during which individuals, businesses, and other stakeholders can provide feedback. Agencies must review and respond to "significant" comments before finalizing a rule. The final rule is then published again in the Federal Register and subsequently incorporated into the Code of Federal Regulations (CFR). A rule can be withdrawn at each step before it is finalized, typically as a result of changes in the priorities and objectives of the administration.

The CFR is the codified collection of all rules and regulations issued by federal departments and agencies. It is organized into 50 titles that group regulations by major subject area. Each title is divided into chapters, which usually bear the name of the responsible agency. Chapters, in turn, are subdivided into parts that cover narrower domains of regulation. For example, Title 12 "Banks and Banking" includes Chapter II "Federal Reserve System," which contains Part 201 "Extensions of Credit by Federal Reserve Banks."

In developing regulations, agencies do not act entirely on their own. The White House, in fact, has ample opportunity to shape the pace and content of major rules. Under Executive Order 12866 (1993), the Office of Information and Regulatory Affairs (OIRA) reviews all significant rules to ensure both compliance with regulatory principles and consistency with presidential priorities.[4] OIRA is a unit within the Office of Management and Budget in the Executive Office of the President. It can formally intervene at two points in the rulemaking process—before the publication of a proposed rule (NPRM) and prior to the issuance of a final rule—though OIRA officials also provide informal feedback at other stages. Following review, OIRA may either return a draft to the agency for reconsideration or allow it to

[4]Section 3(f) of Executive order 12866 of 1993 defines as "significant" those rules with an anticipated annual effect on the economy of at least $100 million, that might adversely affect in a material way the economy, the environment, public health or safety, or lower levels of governments, that might interfere with actions by another agency, that might materially alter the budget, or that raise novel legal or policy issues.

advance to the next stage of the rulemaking process.

2.2 Data on the Rulemaking Process

Information on the regulatory activities of agencies comes from the Unified Agenda of Federal Regulatory and Deregulatory Actions (UA). Published semiannually by the General Services Administration, the UA provides information on all ongoing rulemaking activities across the entire federal government.[5] Each regulatory *process* is identified by a Regulation Identifier Number (RIN), which tracks the process from initiation to completion.[6] A RIN first appears in the UA when an agency begins to work on a rule. The RIN then recurs in subsequent issues of the UA until the process concludes—typically with the publication of a final rule. To provide a concrete example, Appendix Figure A.1 shows the timeline for RIN 2050-AG83—a regulatory process by the Environmental Protection Agency, which lasted from Spring of 2015 to Spring of 2018.

The UA provides two types of information that are particularly useful to us. First, it records a timetable of all actions the agency has taken or expects to take to complete the regulatory process. Panel A of Appendix Figure A.2 shows the initial entry for RIN 2050-AG83 (Spring 2015), where the agency projected publication of a NPRM in July 2015. Panel B shows the final entry (Spring 2018), documenting that the NPRM was published on November 1, 2016, and the final rule was issued and made effective on February 7, 2018. This structure enables us to measure both the overall duration of a regulatory process and the time from initiation to publication of an NPRM.

Additionally, the UA provides detailed information on the characteristics of each rulemaking process. Beyond the responsible agency, it records whether a rule is classified as major, its level of priority, and whether it is likely to affect small businesses under the Regulatory Flexibility Act.[7] Most importantly for our purposes, the UA identifies the regulator(s) who are responsible for the development of the rule.[8] Appendix Figure A.3 shows the UA entry for the two regulators assigned to RIN 2050-AG83.

The final data set for our analysis includes 35,657 regulatory processes initiated between

[5] Only one issue of the Unified Agenda was published in 2012.

[6] Throughout the paper, we use the terms "regulatory process" and "rulemaking process" interchangeably, whereas proposed and final rules are referred to as "regulatory actions."

[7] As per 5 USC § 804(2), a "major rule" is any rule that the agency finds is likely to result in (a) an annual effect on the economy of \$100M or more; (b) a major increase in costs or prices for consumers, industries, government agencies, or geographic regions; or (c) significant adverse effects on competition, employment, investment, productivity, or innovation. Priority levels can be broadly categorized in three categories: economically significant (largely corresponding to major rules), otherwise significant (i.e., other rules falling under OIRA review), other non-significant rules.

[8] Doherty et al. (2019) confirm via interviews with agency officials that the named regulators are either "responsible for overseeing the development and clearance of a rule or its main author" (p. 1627).

the Spring of 1997 and the Fall of 2023, and 14,848 regulators who are assigned to at least one regulatory action during this period.[9]

2.3 Matching Regulators to Voter Registration Records

To identify the ideological preferences of individual regulators, we draw on the work of Spenkuch et al. (2023), who link personnel records for all federal employees to the universe of registered voters in the United States. The latter data come from the non-partisan for-profit data vendor L2, Inc., and include, among other pieces of information, the partisan leaning of all individuals who were registered to vote during at least one election cycle between 2014 and 2020.[10] We match our regulators to their data, relying on a combination of name (first name, last name, and middle name when available), agency, and years in which we observe them working on regulatory processes. To alleviate concerns about measurement error, we assign partisan leanings to regulators only if they are uniquely matched or if they match to multiple voters that share the same party affiliation. Overall, we are able to recover partisan preferences for approximately 56% of the regulators in our data, and about 67% of rules have at least one matched regulator over the lifecycle of the rule (see Appendix Table A1 for details). Appendix Figure A1 reports match rates over time and Appendix Table A2 compares rules with matched and unmatched regulators.

3 Stylized Facts

We begin our empirical analysis by establishing several new descriptive facts about regulators and delegation in the rulemaking process.

3.1 Regulator Characteristics

To compare regulators with other federal employees in the personnel and voter registration records, we restrict the sample to bureaucrats whom we can successfully link to the data of Spenkuch et al. (2023). Table 1 reports summary statistics for regulators (cols. 1–2) and other government workers (cols. 3–4). Panel A focuses on characteristics gleaned from personnel records. Compared to other bureaucrats, regulators enter government service at a younger age, are substantially more educated—58% hold a postgraduate degree compared to just over one-quarter among other bureaucrats—and have considerably longer tenure in

[9] For a summary of data cleaning steps and sample restrictions, see Appendix Table A1.

[10] See Spenkuch et al. (2023), in particular their Online Appendix, for additional details.

federal service. Regulators also earn higher salaries.[11] They are disproportionately based in Washington, D.C. (about two-thirds versus 12% of other federal employees), and only 1% are political appointees, underscoring the technical nature of their positions.[12]

Spenkuch et al. (2023) find that Democrats are significantly overrepresented among all federal bureaucrats. Drawing on our linked data, we show in Table 1, Panel B, that the partisan imbalance among regulators is even more pronounced. Among regulators, 63% are registered as Democrats, compared to 49% of other federal employees. Conversely, only 20.6% of regulators are registered Republicans and 16.2% are independents, whereas the corresponding shares among other federal workers are 29% and 22%, respectively. For comparison, the share of Democrats in the universe of individuals in our voter registration data is 40.8%, while the share of Republicans is 30.7% (Spenkuch et al., 2021). Democrats are thus vastly overrepresented among regulators, both relative to the general population as well as to other bureaucrats.

For each of the major departments and agencies, Figure 2 reports the share of rules that are assigned to regulators with different party affiliations.[13] There is considerable variation in the partisanship of regulators across agencies. In some agencies, such as the Department of Justice, the Department of Housing and Urban Development, or the Securities and Exchange Commission, Democrats are responsible for developing more than 70% of rules. In the Departments of Defense, Agriculture, and Homeland Security, however, a majority of rules are handled by Republicans or independents.

Another defining feature of regulators is their high degree of specialization in particular subject areas. To measure specialization, we calculate, for every regulator, a Herfindahl–Hirschman Index (HHI) based on the distribution of their past rule assignments across title–chapter–parts of the CFR. As explained in the previous section, each part of the CFR corresponds to a narrow domain of regulation. The HHI for a given regulator equals one if that person has worked exclusively on a single title-chapter-part, and it declines to $1/N$ if each of her N previous assignments involves a different part, making the HHI a natural

[11] The five most common occupational categories among regulators are "Miscellaneous Administration and Program Series," "General Attorney Series," "Environmental Protection Specialist Series," "Program Management Series," and "Management and Program Analysis Series." Together, these account for 53% of regulators. By contrast, other federal employees are spread across a wider range of occupations; their five most common categories—"Miscellaneous Clerk and Assistant Series," "Miscellaneous Administration and Program Series," "Nursing Series," "Physician Series," and "Social Insurance Administration Series"—cover only 28% of other bureaucrats.

[12] The share of political appointments among other bureaucrats is even lower, consistent with the less senior and lower-paid roles they typically occupy. After controlling for earnings, regulators and other bureaucrats are about equally likely to serve as political appointees.

[13] The category "Other" includes all departments and agencies with fewer than 500 rules.

measure of specialization for a given person.[14] We then average the individual-level indices by regulators' number of past assignments, using a second-order fractional polynomial to smooth the underlying relationship. Figure 3 shows the result. Irrespective of past workload, regulators' assignments tend to be concentrated in a small number of CFR parts. Consider, for instance, regulators with twenty previous assignments. An HHI of approximately 0.5 corresponds to someone handling 13 rules in one title–chapter–part, 5 in another, and 2 in a third. Such a skewed distribution of past experiences is highly unlikely absent considerable specialization. To demonstrate this point more formally, we benchmark our observed measure of specialization with counterfactual ones under random assignment of regulators and rules, either within agencies (long-dashed lines) or the entire federal bureaucracy (short-dashed lines). Strikingly, even random assignment within the same agency would yield levels of specialization that are *much* closer to random assignment across the entire bureaucracy than to what we actually observe in the data. Our results in Figure 3, therefore, imply that individual regulators specialize in narrow subject areas and, at most, a few parts of the Code of Federal Regulation.

3.2 Delegation and Political Alignment in the Rulemaking Process

Theoretical models of the bureaucracy suggest that principals have an incentive to assign rulemaking responsibilities to bureaucrats whose preferences accord with their own (Epstein and O'Halloran, 1999; Besley, 2007; Lewis, 2008). In practice, however, Democrats are vastly overrepresented among regulators, rulemakers tend to be highly specialized, and organizational norms discourage overt partisan bias. These constraints may limit the extent to which agency leaders can achieve partisan alignment. In the remainder of this section, we examine how often rulemaking is, in fact, delegated to aligned versus misaligned regulators.

To this end, Figure 4, Panel A, shows the total share of rules that are assigned to Democratic, Republican, and independent regulators over time. Although new presidential administrations quickly replace agency heads and other political appointees with copartisans (see Bolton et al. 2020; Spenkuch et al. 2023), the evidence in this figure indicates that misaligned regulators are not replaced to nearly the same extent. Even during the George W. Bush and Trump administrations, more than 60% of all regulatory processes were delegated to Democratic rulemakers.

Motivated by the surprising absence of marked partisan cycles across all regulatory processes, Panel B of Figure 4 focuses on newly initiated "major" rules.[15] If partisan alignment is at all important to agency heads and political appointees, then we would expect to see

[14] By construction, regulators with only a single past assignment have an HHI of one.

[15] Among the 35,657 regulatory processes in our dataset, 3% are classified as "major."

significant swings when the stakes are highest and when leaders are not constrained by pre-existing assignments of regulators to rules. Although the data become much noisier due to the small number of new major rules each year, this is, indeed, what we find.

In order to quantify the extent of partisan swings more precisely, we estimate variants of the following econometric model:

$$\text{Share Democratic Regulators}_{r,t} = \alpha + \beta \text{Democratic President}_t + X_r^{\prime}\theta + \epsilon_{r,t}. \tag{1}$$

Here, Share Democratic Regulators$_{r,t}$ denotes the share of Democrats on the team of regulators assigned to rule r at time t. Democratic President$_t$ is an indicator for the party of the president, and X_r corresponds to a comprehensive vector of rule-level controls. The latter includes the predicted duration of the rulemaking process (see Appendix subsection B), the number of assigned regulators, the importance and priority of the rule, and whether the rule falls under the Regulatory Flexibility Act (RFA). Since the UA allows us to track the progress of each rule over time, we can estimate ancillary models that also include a rule fixed effect. In the respective specifications, all identifying variation comes from within-rule over-time changes in the party controlling the presidency.

The estimates in Table 2 confirm the existence of partisan cycles in the delegation of rules to regulators. In the baseline specifications (cols. 1–2), the share of Democrats (Republicans) working on the average rule increases by about two percentage points when a Democratic (Republican) administration takes office. While these shifts are modest in size, with t-statistics near or above four, the respective coefficients are estimated very precisely. Columns 3–4 distinguish between all newly initiated rules and major ones. For major rules in particular, partisan cycles are five to seven times larger than the average, consistent with the idea that political alignment matters most when the stakes are high and agency heads have discretion. Finally, columns 5–6 introduce agency and rule fixed effects. The results in these columns indicate that new administrations alter at least some pre-existing assignments.

Taken together, our findings suggest that while partisanship does shape the delegation of rulemaking responsibilities, alignment effects are concentrated in high-stakes contexts, and even then, they are far from complete. As a result, even important pieces of new regulation are frequently delegated to bureaucrats who are politically misaligned with the current administration.

4 Political Alignment and the Speed of Rulemaking

The descriptive findings in the previous section suggest that partisan alignment plays a limited role in the delegation of rulemaking responsibilities. This, in turn, raises the question of whether alignment actually matters for regulatory outcomes.

An important empirical challenge in studying the effects of political alignment is that regulator assignments are not as good as random. For instance, the results above imply that important rules are disproportionately delegated to aligned regulators (see also Appendix Table A3, Panel A, columns 1–2). If important regulatory processes exhibit systematically different outcomes, then naïve comparisons of rules that were overseen by aligned and misaligned agents may produce misleading results. Moreover, principals may make assignment decisions based on agent characteristics that directly affect outcomes. If aligned regulators differ in terms of, say, experience, seniority, or competence, then observed differences in rulemaking outcomes might be driven by regulator quality rather than political alignment.

Our analysis addresses these concerns in several ways. First, for outcomes that are observed repeatedly over the life of a rule, we exploit within-rule variation in regulator alignment. By relying solely on within-rule variation, we eliminate confounding due to cross-sectional differences in rule characteristics, regulator composition across agencies, and potential outcomes. Second, for outcomes that are realized only once per rule, we exploit within-regulator (or regulator-team) variation in alignment across rules, thereby holding constant any time-invariant attributes of regulators that might influence outcomes. In particular, our regulator-team fixed effects account for the possibility that certain types of regulators are systematically more likely to be assigned to rules with particular outcome profiles. Third, we leverage the richness of our data to explicitly account for additional rule- and regulator-specific factors. Reassuringly, we show in Appendix Table A3, Panel A, that, conditional on our controls, rule characteristics no longer predict the alignment status of the assigned regulators.

4.1 Political Alignment and Rule Completion

There exists substantial variation in how quickly rules move through the bureaucratic process. While the average duration from rule initiation to completion is 654 days, the interquartile range equals 765 days. As a consequence, many regulatory processes span multiple presidencies.

Since excessive delays can and do prevent administrations from enacting their policy priorities, we first ask whether political alignment affects the speed of rulemaking. To study this question, we construct a dataset at the rule-year-month level and conduct a duration analysis. Our sample for this analysis consists of all rules that we can match to individual regulators and that have clearly defined start and completion dates—for a total of 15,834 rules and 390,239 rule-year-month observations.[16]

To assess the connection between political alignment and the speed of rulemaking, we estimate a discrete-time hazard model of rule completion. Specifically, we model the hazard that rule r is completed in month t as

$$\text{Completed}_{r,t} = \beta \text{Share Aligned}_{r,t} + X^{'}_{r,t}\delta + \alpha_r + \gamma_{r,t} + \varepsilon_{r,t}, \tag{2}$$

where $\text{Completed}_{r,t}$ corresponds to an indicator for whether rule r is completed in month t, $\text{Share Aligned}_{r,t}$ measures the fraction of regulators assigned to rule r in month t who are copartisans of the president, and $X_{r,t}$ includes additional rule-level controls interacted with duration fixed effects, including priority status, major-rule status, RFA status, the number of assigned regulators, and predicted time to completion (see Appendix B).[17,18] To absorb unobserved heterogeneity across rules, time, and agencies, we also include a rule (α_r) and an agency-by-start-time-by-duration fixed effect ($\gamma_{r,t}$).

Intuitively, our duration analysis asks whether rules that are overseen by a larger fraction of contemporaneously aligned regulators are differentially likely to be completed in any given month, comparing only rules initiated by the same agency in the same year-month after the same amount of time has elapsed. Since reassignments of regulators are rare, within-rule variation in political alignment is almost entirely driven by presidential transitions.[19]

Table 3 reports results from estimating variants of the hazard model above. In column 1, we first relate the probability of rule completion to the contemporaneous share of aligned regulators. The positive estimate in this column indicates that rules are significantly more likely to be completed in periods with greater alignment. Column 2 introduces duration-specific rule-level controls. If anything, these controls slightly increase the coefficient of interest.[20] Finally, column 3 additionally accounts for the expertise of the assigned regulators, as mea-

[16] Since we define the start of a regulatory process as the date it was first published in the Unified Agenda, for a rule to have an observable end date it must have been completed before the end of our sample period and appear at least in two UA publications. For additional details on sample sizes and restrictions, see Appendix Table A1, Panel B.

[17] Following standard practice in hazard analyses, rules completed in t exit the risk set in $t+1$

[18] For single-regulator rules, $\text{Share Aligned}_{r,t}$ is binary. We obtain qualitatively similar results when restricting attention to single-regulator rules or to rules that were initiated either under full alignment or full misalignment.

[19] Approximately 74% of all rules are overseen by the same set of regulators throughout the entire rule-making process.

[20] The observed change in the point estimate is consistent with the fact that aligned regulators tend to be assigned to rules that revise more complex parts of the CFR (see Appendix Table A3, Panel A), which takes longer to complete.

sured by the share of team members who have previously worked on rules pertaining to the same parts of the CFR. Across all three specifications, we find that full alignment increases the probability of rule completion by 8–10% relative to the unconditional completion rate of about 3.8% in a given month.

Since rules can be completed either by being finalized or withdrawn, we examine in columns 4–5 whether alignment is associated with higher failure or success rates. Interestingly, we do not find that contemporaneous alignment of regulators results in rules being withdrawn at different rates. Instead, our results suggest that partisan alignment increases the likelihood that a rule is finalized and, thus, modifies the CFR.

We show in Appendix Table A4 and Table A5 that the results above are qualitatively robust to restricting our sample to rules that were initially assigned only to (mis)aligned regulators. The results are also robust to restricting the sample to rules that are delegated to a single regulator, and to discarding variation in alignment due to reassignments. Finally, we also test for heterogeneity by partisanship. Comparing Democratic and Republican regulators to independents, we obtain estimates that are of comparable size and statistically indistinguishable.

4.2 Political Alignment and OIRA Review

We now complement the previous analysis focusing on reviews of rules conducted by the Office of Information and Regulatory Affairs (OIRA). Situated in the Executive Office of the President, OIRA reviews are a key tool through which the White House can align the content of proposed and final rules with its priorities. They function as a "check in the rulemaking efforts of career agency officials" (Yackee, 2019). If the content of the rule differs depending on the political ideology of the regulator, we expect alignment to be predictive of the speed of OIRA reviews.

All major rules—rules with an estimated economic impact of more than $100 million—, as well as those otherwise deemed relevant by the administration, must undergo the review process at OIRA. Although the vast majority of rules ultimately pass this step, there exists significant variation in how long the review process takes. While the average OIRA review takes 71 days, the interquartile range is 67. OIRA reviews can occur at two points in the rulemaking process, either before the notice-and-comment period or before the publication of the final rule. This institutional feature allows us to implement a within-rule research design similar to the one above.

Table 4 relates the overall duration of OIRA review with the alignment status of the assigned regulators at the time a rule is submitted for review. In addition to the rule-level controls listed in the previous sections, we control for indicators for the agency and time of rule initiation, as well as the agency and time of OIRA review. The resulting comparisons are thus between rules that were initiated by the same agency and in the same year-month, as well as between rules from the same agency that are submitted for OIRA review at the same time. Consistent with our results in the previous table, we find that a higher share of politically aligned regulators expedites the review. This holds both in the most parsimonious specification (column 1) as well as conditional on rule-level and experience controls (columns 2–3). Exploiting the fact that some rules undergo OIRA review more than once, the results in column 4 show that within-rule over-time changes in alignment are associated with significantly shorter review periods.

Finally, we ask if alignment predicts whether OIRA submissions are withdrawn or returned (column 5). Consistent with the fact that only 6.4% of rules are withdrawn or returned to the rulewriting agency, we find no evidence to suggest that alignment affects the extensive margin of OIRA review. Overall, the fact the review process takes longer when it involves misaligned rulemakers is suggestive of either greater suspicion on the part of OIRA, a higher frequency of (perceived) problems with the rule, or both.[21]

5 Political Alignment and Regulatory Outcomes

Our results thus far suggest that political alignment between regulators and the president is conducive to faster rulemaking. Since speed may come at the expense of quality, we now ask whether rules that were overseen by aligned regulators exhibit systematic differences in other, quality-related dimensions. Given the dearth of direct and comparable measures of quality, we examine several plausibly quality-related outcomes that, taken together, provide a consistent picture of the costs of political misalignment to the principal.

5.1 Political Alignment and Public Support

Public participation is a core principle of the Administrative Procedure Act, meant to promote transparency and accountability in agency rulemaking (Haeder and Yackee, 2015). During the notice-and-comment period, citizens, organizations, and other interested parties may submit feedback on proposed rules—often in the form of expressions of support

[21] Appendix Table A6 presents robustness checks involving different subsamples. We find qualitatively similar effects when restricting attention to fully aligned or fully misaligned teams of regulators (column 2) and when focusing on rules assigned to single regulators (column 3). Interestingly, however, we also find that the observed alignment effects are driven by Democrats (column 4). For Republicans, the point estimate is economically small and not statistically distinguishable from zero (column 5).

or opposition, or by providing additional evidence and recommendations for the agency to consider. While agencies are not required to adopt recommendations and criticisms, they must respond to what the courts have deemed "significant" comments before finalizing a rule (Garvey, 2017; Yackee, 2019).

In addition to promoting transparency, public comments create a large body of unstructured text that we use to measure public support for proposed rules. Since 2003, members of the public have been able to submit comments electronically through `Regulations.gov`, the main platform where agencies post regulatory materials and solicit feedback. We scrape `Regulations.gov` and link all available comments to our data on rules, for a final analysis sample of 5,297 commenting processes (NPRMs) and more than six million comments (Appendix Table A1).

Two-thirds of proposed rules received at least one comment, with an average of 874 comments per rule. To determine whether a particular comment expresses support or opposition, we build on recent advances in machine learning. Specifically, we rely on stance detection and natural language inference (NLI) models designed for entailment classification tasks. These models estimate the probability that a document *entails* a given statement. For example, the comment "I fully support the EPA initiative" has a high probability of entailing the statement "The author of this comment *supports* the proposed rule." NLI works by taking a premise (i.e., the text of a comment) and a set of hypotheses (e.g., "The author *supports*, *opposes*, or *is neutral toward* the proposed rule") and identifying which of the hypotheses is most likely to be true (see, e.g., Burnham, 2024).[22] Overall, this approach classifies 36% of comments as conveying a negative stance towards the proposed rule, whereas 32% are classified as supportive. The remaining comments are neutral.

We measure overall public support for a proposed rule by grouping comments at the rule level and computing the share of comments with positive and negative stances. We then test whether rules overseen by misaligned bureaucrats attract greater criticism. To do so, we relate the share of supporting and opposing comments to the share of regulators who were politically aligned with the president when the rule was initiated.

Because most rules undergo only a single round of commenting, we can no longer make use of within-rule variation in alignment. Instead, we address concerns about non-random regulator assignment by exploiting within-regulator-team variation in alignment. More specifically,

[22] Our approach improves on standard sentiment analysis, as research shows that stance need not be correlated with sentiment (Bestvater and Monroe, 2023). In subsubsection A7 in the Appendix, we report several examples of comments classified as positive, negative, or neutral in stance, and how stance relates to sentiment polarity.

we estimate:

$$y_r = \beta \text{Share Aligned}_{\Lambda,r} + X_r'\gamma + \theta_\Lambda + \varepsilon_r, \tag{3}$$

where y_r denotes the outcome for rule r (e.g., the share of comments with a negative stance), and Share Aligned$_{\Lambda,r}$ denotes the share of regulators on the initially assigned team (Λ) that were copartisans of the president when rule r was initiated. X_r is a vector of rule-level characteristics, which include indicators for the agency and time of rule initiation.

The key empirical challenge in this setting is nonrandom assignment of regulators to rules. As Appendix Table A3, Panel A, shows, aligned teams are more likely to be assigned to significant or major rules. While controlling for observable rule characteristics helps to address some endogeneity concerns, it does not account for unobserved factors that are correlated with both the alignment status of regulators and public support for the rule. For this reason, the specification in eq. (3) also includes regulator-team fixed effects, θ_Λ. By comparing rules that were handled by the same team of regulators across periods in which they were aligned rather than misaligned due to turnover in the White House, these fixed effects purge time-invariant differences in teams' portfolios (e.g., specialization), which may bias cross-sectional comparisons. Identification thus comes from within-regulator-team variation after accounting for potential agency–time shocks.[23]

Table 5 reports our results. Column 1 shows that rules overseen by aligned regulators attract fewer opposing comments. On average, 36% of comments entail a negative stance, but alignment is associated with a 3.2 percentage point reduction in opposition. Columns 2–3 add rule-level controls and a control for the experience of the team of regulators. If anything, accounting for rule characteristics implies slightly larger effects of alignment. Finally, the last column studies the extent to which comments are positive and supportive of the rule (as opposed to negative or neutral). As column 4 shows, political alignment is associated with an increase in the likelihood of a rule being supported. Taken together, the results in Table 5 provide evidence that rules developed by aligned regulators are met with less opposition from interest groups and the broader public. From the principal's perspective, alignment thus carries benefits beyond faster completion.[24]

[23]Consistent with the assumption that the residual variation in alignment is as good as random, Appendix Table A3, Panel A, shows that, after conditioning on fixed effects, regulators' alignment status is statistically unrelated to observable rule characteristics.

[24]Appendix Table A7 reports robustness checks. Again, we obtain qualitatively similar results when restricting attention to rules assigned to fully (mis)aligned teams or only a single regulator. We also obtain similar point estimates when comparing Democratic and Republican regulators to independent. Interestingly, however, we do not find that alignment is predictive of the total number of comments (Appendix Table A8).

5.2 Political Alignment and Impacts on Federal Regulation

Our finding that political alignment shapes the public perception of proposed regulation raises the question of whether its influence extends to the actual text of final rules, as codified in the CFR. The CFR records the operative language of all federal regulations, making it a natural setting to examine whether alignment affects the way rules are written.

We test for alignment effects by mapping each rule to the CFR sections it revises. For every regulatory action, we identify the final rule published in the Federal Register and extract its full text. The Federal Register includes a summary of the rule, its effective date, background on the action, a discussion of public comments, and a summary of the agency's analyses. Most importantly for our purposes, the Federal Register also specifies the CFR sections that are amended by the rule. This information allows us to compare the text of each affected section before and after codification.[25] Our analysis of the CFR covers 129,260 sections amended by 10,837 rules.[26]

To examine whether political alignment leaves an imprint on the CFR, our empirical specification relates post-revision outcomes of affected sections to the alignment status of the regulators who developed the rule:

$$y_{i,p,r}^{Post} = \beta \text{Share Aligned}_{\Lambda,r} + \alpha y_{i,p,r}^{Pre} + X_r'\gamma + \theta_\Lambda + \tau_p + \varepsilon_{i,r}, \tag{4}$$

where $y_{i,p,r}^{Post}$ measures the post-revision outcome for section i of CFR title-part p affected by rule r, and $y_{i,p,r}^{Pre}$ is the corresponding pre-revision quantity. As before, Share Aligned$_{\Lambda,r}$ denotes the share of regulators on team Λ that were aligned with the president at the time of rule initiation, and X_r is a vector of rule-level controls. In addition to the covariates from our duration analysis, X_r also contains agency-by-time indicators for both initiation and effective dates. These indicators help to account for agency- and time-specific shocks that may correlate with the alignment of regulators.

We again include regulator-team fixed effects, θ_Λ, to address nonrandom assignment of regulators to rules. These fixed effects restrict comparisons to rules handled by the same regulators, with variation in alignment arising only through presidential turnover. In addition, we include CFR title-part fixed effects, τ_p, which absorb persistent differences across related sections of the CFR—a part has, on average, about 100 sections—and thereby guard against the possibility that aligned regulators are disproportionately assigned to parts of the CFR that are more or less challenging to revise.

[25] When multiple rules revise the same section in the same year, we reweight the data to assign equal weight to each rule.

[26] See Appendix A4 for details.

Since the regulatory processes in our data pertain to a diverse set of issues and industries, it is difficult to measure the content of a rule in a manner that is easy to interpret and comparable across contexts. There are, however, widely accepted standards for clear writing; and the Plain Writing Act of 2010 requires federal agencies to use clear, concise, and well-organized language. Thus, to make progress in assessing the impact of political alignment on the quality of regulations, we focus on their readability. We measure readability using standard indices from computational linguistics. Our main measure, the Flesch score, combines sentence length (i.e., words per sentence) and word complexity (i.e., syllables per word) into a unidimensional index (Flesch, 1948).[27] In the analysis below, we rely on the Flesch score as our baseline measure and confirm that the results hold across a broad set of alternative readability indices.

Table 6 shows results from estimating variants of the model in equation 4. Columns 1–3 focus on the Flesch score, standardized to have a mean of zero and a standard deviation of one. Comparing sections revised by the same team of regulators, rules developed under greater alignment have more readable text (col. 1). The point estimate remains nearly unchanged when adding rule-level controls (col. 2), and when controlling for regulator experience, as measured by the share of team members who have previously prior work on the same title-part (col. 3). Columns 4–5 turn to the components of the Flesch score. The results in these columns show that the estimates in the first three columns are driven by shorter sentences, rather than differences in word complexity. Overall, we find that political alignment is associated with a 0.03 SD increase in readability. While this may, at first glance, appear to be a trivial improvement, it is important to note that the outcome is measured at the title-part-section level of the CFR and that most rules modify only a small portion of each section. It is, therefore, remarkable that the change in readability is large enough to be statistically detectable.

For the estimates in Table 6 to have a causal interpretation, the initial alignment of regulators must, conditional on our controls, be as-good-as-random. Appendix Table A3, Panel B, shows that alignment is only weakly correlated with the observable characteristics of CFR sections. If anything, aligned regulators are assigned to rules that modify sections of the CFR with *more*-complex words. We would, therefore, expect omitted variables bias to work against finding a positive impact of alignment on readability.

Appendix Table A10 and Table A11 report a series of robustness and heterogeneity checks. The results therein show that our readability results materialize in various cuts of the data and that they are robust to winsorization. Importantly, we demonstrate in

[27] Specifically, the Flesch score is computed as `Flesch = 206.835 - 1.015 (words/sentence) - 84.6 (syllables/word)`. See also Appendix A6.

Figure 5 that alternative measures of readability produce qualitatively similar conclusions. More specifically, Figure 5 reports alignment effects from estimating the regression model in column 3 of the previous table, using 47 alternative readability indices as outcomes. Only 7 of these indices produce negative point estimates, while 32 others yield positive and statistically significant coefficients. Taking the standardized average across all scores, we continue to find that greater alignment is associated with greater readability of the revised section.

5.3 Political Alignment and Legal Challenges

The evidence so far suggests that rules overseen by misaligned regulators (i) take longer to complete, (ii) are more likely to attract opposition, and (iii) tend to be lengthier and less readable. Although these findings imply that political misalignment is detrimental to the principal, it remains unclear whether the resulting rules are, in fact, of lower quality. For example, it could be the case that greater textual complexity is indicative of higher precision and legal accuracy, in which case misaligned rulemakers might produce regulations that are overall better.

In order to provide additional evidence on the consequences of agency frictions, we analyze court challenges. Federal lawsuits are a common way for interest groups to challenge new regulations. Given the costs associated with lodging federal lawsuits, basic economic theory suggests that the propensity to challenge a rule in court increases with the perceived probability of success (Shavell, 2009). If regulatory processes overseen by misaligned regulators are more likely to be legally defective, then we would expect this problem to manifest in a greater frequency of litigation.

Our analysis of legal challenges draws on a database compiled by the Institute for Policy Integrity, which tracks federal lawsuits against all major rules—those with an annual economic impact of at least $100 million—finalized between 1993 and 2023. For each rule, legal experts coded whether it was subject to at least one federal lawsuit. Beyond recording the incidence of litigation, the database also documents the grounds on which courts evaluate challenges. Many opinions invoke the "Chevron doctrine," under which courts assess whether an agency has acted within its statutory authority; and roughly a third of opinions find rules to be arbitrary and capricious, meaning the agency failed to act within the bounds of reason and legality.[28] In order to assess whether rules developed by misaligned regulators are more likely to be challenged in court, we use the same within-regulator-team research design as in Section 5.1 above.

[28] For example, in Independent Contractor Status Under the Fair Labor Standards Act; Withdrawal, 86 Fed. Reg. 14,027 (Mar. 12, 2021), plaintiffs successfully argued that the Department of Labor's actions were arbitrary and capricious.

Table 7 presents the results. Almost a quarter of all major rules are subject to lawsuits. Rules that are (at time of initiation) assigned a larger share of aligned regulators, however, are 5.2 p.p. less likely to be challenged in court (column 1). Since our baseline specification relies only on comparisons of rules that were issued by the same agency in the same year, this finding cannot be attributed to certain agencies facing more litigation under certain administrations.[29,30] Columns 2–4 probe the robustness of the point estimate to including more stringent controls and fixed effects. If anything, however, the estimated effect of alignment increases, especially when including regulator-team fixed effects. While the estimate in column 4 is admittedly imprecise—given the relatively small number of major rules that were developed by the same teams—even the lower bound of the associated 95% confidence interval implies an economically sizeable effect.[31]

Based on the evidence in Table 7, we conclude that rules overseen by aligned regulators are less likely to be challenged in court. Taken together, the results in this section suggest that agency frictions due to misalignment not only slow down the regulatory process but also result in lower-quality rules—-at least along some dimensions.

6 Trade-off Between Alignment and Expertise

Our findings imply that misalignment between regulators and their political principals carries significant costs. Rules overseen by misaligned regulators take longer to complete, attract more pubic opposition, are less readable once codified, and face a higher likelihood of legal challenges. This raises an important question. If misalignment is costly, why do agency heads and political appointees often delegate rulemaking responsibilities to regulators who are misaligned?

In what follows, we show that principals value regulators' expertise more than political alignment. Yet expertise is concentrated in a relatively small number of individuals. When the most knowledgeable regulators are not politically aligned, then the principal faces a trade-off. She can delegate to an aligned regulator and sacrifice expertise, or assign the rule to an expert who does not necessarily share her goals.

[29] Raso (2015) argues that agencies with lower litigation risk are more likely to strategically change the rule-making process, for instance by avoiding the notice-and-comment phase. Such cross-agency differences are likewise accounted for by our fixed effects.

[30] Unfortunately, the small sample size and limited variation in the outcome prevent us from concluding that the success rate of challenges varies by alignment. Overall, only about 30% of the challenges are successful in court.

[31] Appenix Table A12 replicates the results above in different subsamples of rules.

6.1 Expertise Trumps Alignment in the Assignment of Regulators

The fact that even important pieces of new regulation are frequently assigned to politically misaligned regulators can be interpreted in two ways. One possibility is that partisan alignment is not particularly important to agency heads relative to other regulator characteristics. An alternative interpretation is that organizational constraints prevent principals from achieving their desired level of alignment. To better understand the role of alignment in the delegation process, we contrast it with expertise. We study this trade-off by examining the assignment decisions of principals at the "choice level."

For each regulatory process r, we identify the set of potential regulators $i = 1, \ldots, N_r$ who could be assigned to oversee it. A regulator i is defined as a potential candidate if she (i) works in the agency where the process is initiated and (ii) is observed writing rules both before and after rule r. We say that regulator i possesses the requisite technical expertise for rule r if she has previously developed a rule pertaining to the same substantive area of regulation. To infer subject areas, we rely on the title-parts of the CFR that rule r seeks to amend.[32] On average, the rules in our data amend 2.5 title-parts. We then construct an indicator equal to one if regulator i has worked on at least one of the same title-parts in the past. For the average rule, only 13% of potential regulators meet this criterion, reflecting the highly specialized nature of rulemaking.

Given this measure of technical expertise, we run a horse race between expertise and political alignment in explaining assignment decisions:

$$d_{i,r} = \beta \text{Aligned}_{i,r} + \gamma \text{Expertise}_{i,r} + \theta_r + \varepsilon_{i,r}. \tag{5}$$

Here, $d_{i,r}$ is an indicator for whether potential candidate i is assigned to rule r, $\text{Aligned}_{i,r}$ corresponds to the alignment status of i at the time of rule initiation, and $\text{Expertise}_{i,r}$ denotes our rule-specific, binary measure of her technical qualification. The rule fixed effect θ_r restricts comparisons to potential candidates for assignment to the same rule.

Table 8 reports results from estimating variants of the regression model in eq. (5). Column 1 includes only rule fixed effects, while columns 2 and 3 additionally control for the number of regulators' past rule-writing assignments as well as regulator fixed effects. Across specifications, regulators with relevant technical expertise are significantly more likely to be assigned to a rule. The magnitude of this effect is two orders of magnitude larger than that of political alignment. In fact, the coefficient on alignment becomes statistically insignificant after conditioning on regulator fixed effects (column 3). In column 4, we test for a

[32]Recall, the CFR is organized into 50 titles representing broad policy domains, each subdivided into parts that cover specific regulatory areas.

potential complementarity between expertise and political alignment. The estimates suggest that aligned regulators are only more likely to be assigned to a rule when they possess the necessary expertise. In other words, agency heads and political appointees appear to value political alignment, provided that it does not come at the expense of expertise.[33]

6.2 Quantifying the Trade-Off between Expertise and Alignment

Building on our measure of regulators' technical expertise, we can perform a back-of-the-envelope quantification of the trade-off between expertise and alignment in the aggregate. For each rule, we identify whether at least one potential regulator possesses the relevant expertise. This set reflects the stock of expertise available to a principal focused on maximizing technical capacity. We then ask whether at least one of these experts is politically aligned. If so, then the principal can achieve both expertise and alignment for that rule. If not, prioritizing alignment would require giving up expertise.

We find that the second scenario is quite common. Among the 33,413 rules that were initiated between 1997 and 2023, principals could delegate to at least one expert in 25,190 cases (75%). In only 18,983 cases (57%), however, could they assign an expert who was politically aligned. Thus, delegating solely to aligned regulators would have entailed a loss of expertise in about 18% of regulatory processes.

As an alternative, we also consider a more refined measure of expertise, which allows us to more precisely estimate the potential loss from delegating only to aligned regulators. To that end, we construct an expertise score that gives greater weight to regulators with more past experience on the same title-parts of the CFR as rule r. Specifically, for rule r touching on a total of Sr title-parts, we define

$$\text{Expertise Score}_{i,r} = \frac{1}{Sr}\sum_{s=1}^{S_r} \text{Previous Assignments}_{i,s},$$

where Previous Assignments$_{i,s}$ denotes regulator i's number of previous assignments to rules that affect title-part s. We top-code this value at 10. Our expertise score should thus be interpreted as measuring regulator i experience across *all* the subject areas of rule r, ranging from 0 (no relevant experience) to 10 (substantial experience with every relevant title-part).

For each rule, we identify the regulator with the highest expertise score, both in the full pool of potential candidates and in the subset of aligned candidates. Panel (a) of Figure 6

[33] Table 8 focuses on the *initial* assignment of regulators to rules (i.e., the first time the rule appears in the UA). Appendix Table A13 reports similar results when we allow for reassignments by extending the analysis to all semesters of rule development. Appendix Table A14 assesses robustness to measuring expertise continuously, i.e., as the share of affected CFR title-parts on which the regulator has prior experience.

depicts the distribution of expertise score for the most qualified individuals in each of these two groups.[34] The distribution for aligned regulators is shifted visibly to the left, indicating that principals who limit delegation to aligned candidates draw from a much less experienced pool.

Panel (b) of the same figure shows the gap in expertise between the best available regulator and the best aligned regulator. For 63% of rules, the two coincide; so principals could delegate to an aligned regulator without sacrificing expertise. For the other 37% of rules, however, the most expert regulator is misaligned. While some of these gaps are modest, they exceed the equivalent of two prior assignments to all relevant subject areas of a rule in about 24% of cases.

To quantify the "total loss" of expertise for a principal who is only willing to delegate rulemaking responsibilities to aligned regulators, we sum the observed gaps across all rules initiated between 1997 and 2023. We then compare this sum to the total stock of expertise that is available to a principal who always delegates to the most qualified regulator, i.e., the one with the highest expertise score. We find that the aggregate gap amounts to nearly 120,000 prior assignments to different title-parts of the CFR, which, in turn, corresponds to approximately 36% of maximal available expertise over the same period of time.

7 Conclusion

Regulation is a cornerstone of modern governance. Elected officials set broad objectives, and individual regulators turn those objectives into binding rules that structure both economic and social life. Delegation to unelected bureaucrats, however, entails a fundamental trade-off between expertise and control. Regulators possess the specialized knowledge needed to design complex rules; yet they may not share the policy preferences of their political superiors. Although such agency problems play a central role in formal theories of bureaucracy, our knowledge of how they manifest in different stages of the regulatory process remains limited. The absence of empirical evidence on this question reflects, at least in part, a lack of adequate data connecting individual regulators to the specific rules they are asked to develop.

In this paper, we begin to open the black box of the regulatory process. Combining data on U.S. rulemaking with personnel and voter registration records, we study how political alignment between regulators and the president shapes regulatory outcomes.

Our findings point to significant agency frictions within the U.S. federal bureaucracy. While expertise remains the dominant factor in assigning regulators to rules, political leaders

[34] We focus on the initial assignment of regulators to rules. Results using the full set of rule–year–month observations, which allow for reassignment over the life of a rule, are nearly identical.

do show a preference for delegating rulemaking responsibilities to aligned officials. Yet uneven partisanship, combined with regulator specialization and scarce expertise, limits the extent to which agency heads and political appointees can consistently delegate to political allies. As a result, even important regulations are often developed by bureaucrats who are misaligned with the administration in power.

From the perspective of the principal, political misalignment is associated with significant costs. Rules overseen by misaligned bureaucrats take systematically longer to complete and attract more opposition during the public commenting process. Political misalignment even manifests in the Code of Federal Regulations. Leveraging tools from computational linguistics, we show that misaligned regulators produce rules that are more verbose, and thus make the CFR more difficult to read. Perhaps most importantly, we also provide evidence that rules developed by misaligned regulators are more likely to be challenged in court.

Taken together, our findings are inconsistent with a "Weberian bureaucracy," in which regulators act as neutral technocrats who efficiently implement the policy objectives of their political superiors.[35] Instead, our results imply that political alignment and agency frictions play an important role in the rulemaking process in the United States.

Our research also points to open questions. Although partisan misalignment imposes costs on political leaders, its welfare implications are *a priori* ambiguous. Even in the absence of a trade-off between partisanship and expertise, political frictions in rulemaking may be socially desirable insofar as they constrain executive power. Understanding the balance between political control and bureaucratic independence remains thus an important question for empirical research. Future research might also explore the broader consequences of political misalignment for economic and social outcomes.

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[35] Max Weber famously argued that "bureaucracy develops the more perfectly, the more it is 'dehumanized,' the more it completely succeeds in eliminating [...] all purely personal elements" (Weber 1922).

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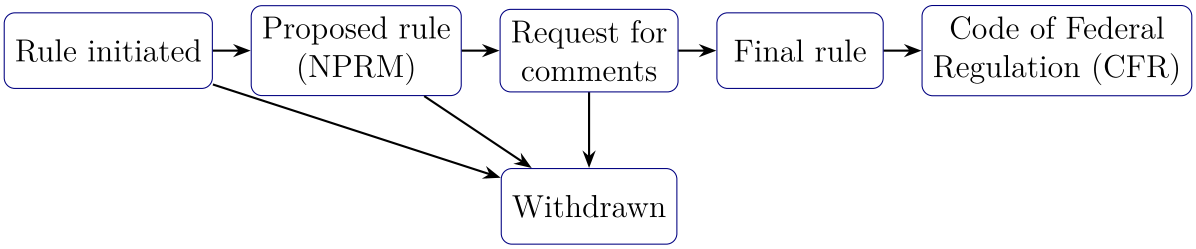
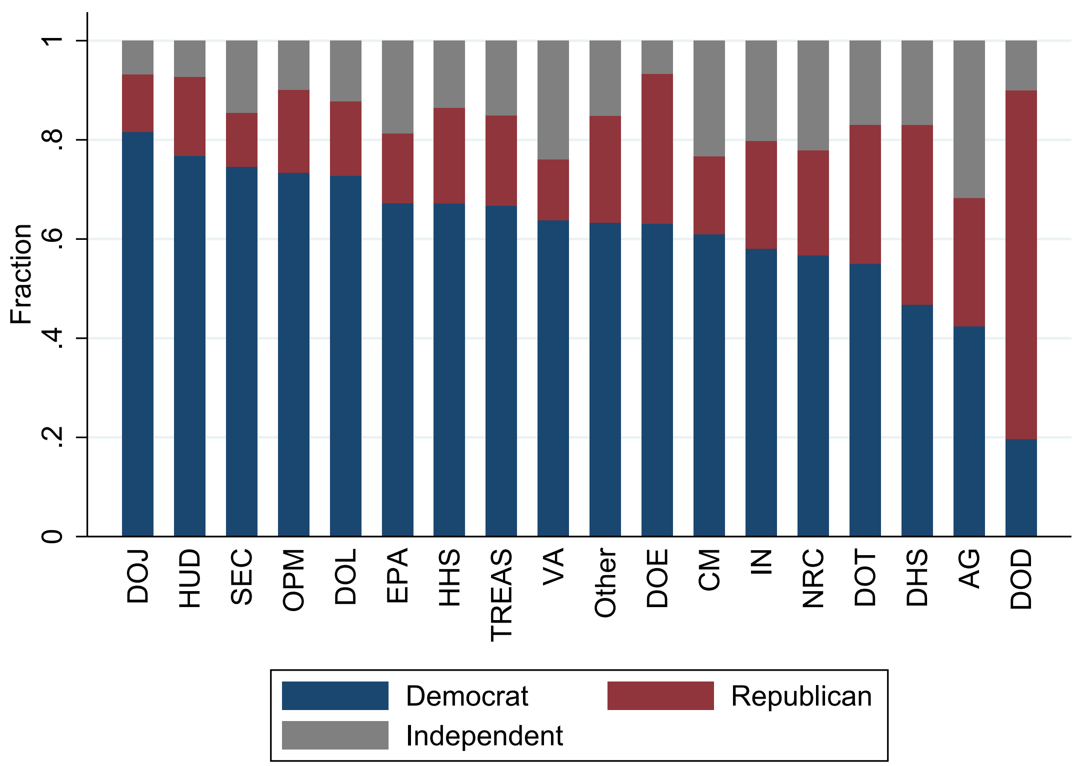
Figures

Figure 1: Rulemaking Process in the U.S.



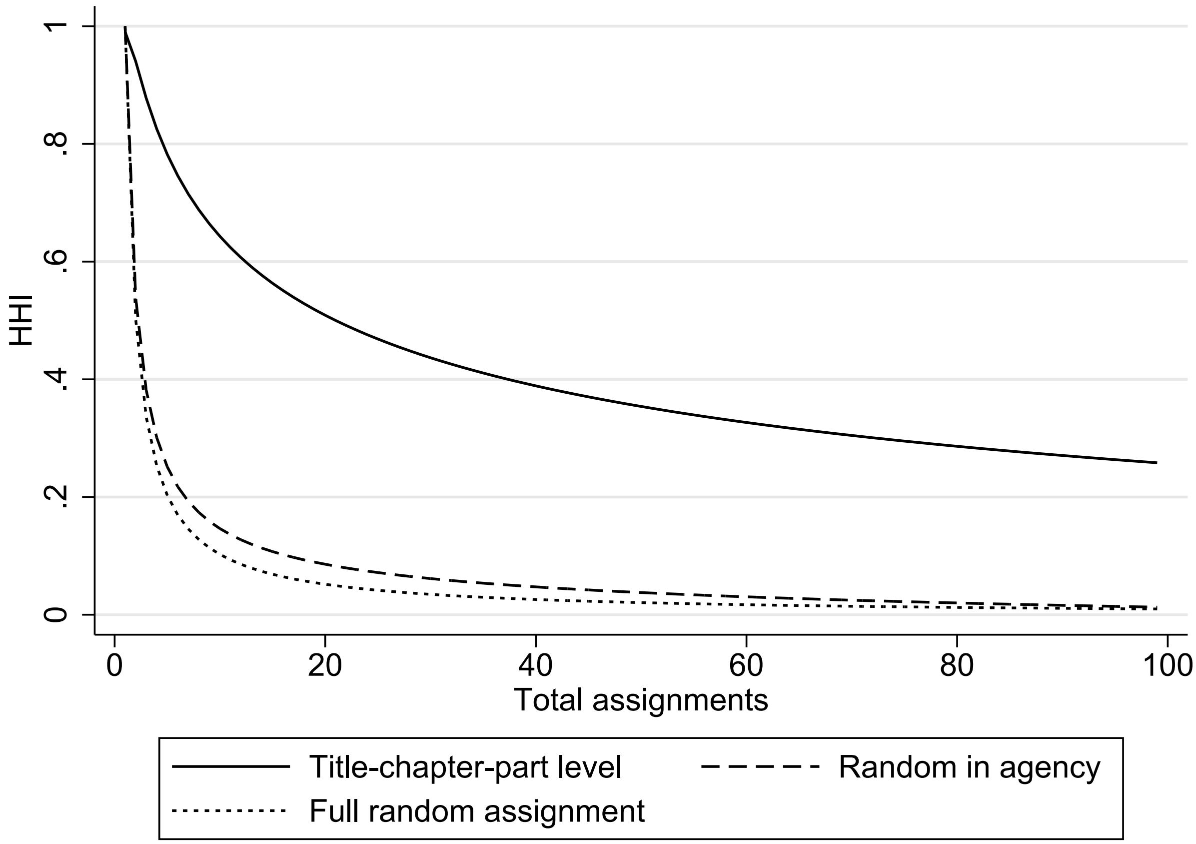
Notes: Diagram shows the typical stages of a rulemaking process in the U.S.

Figure 2: Party Affiliation of Regulators, by Department



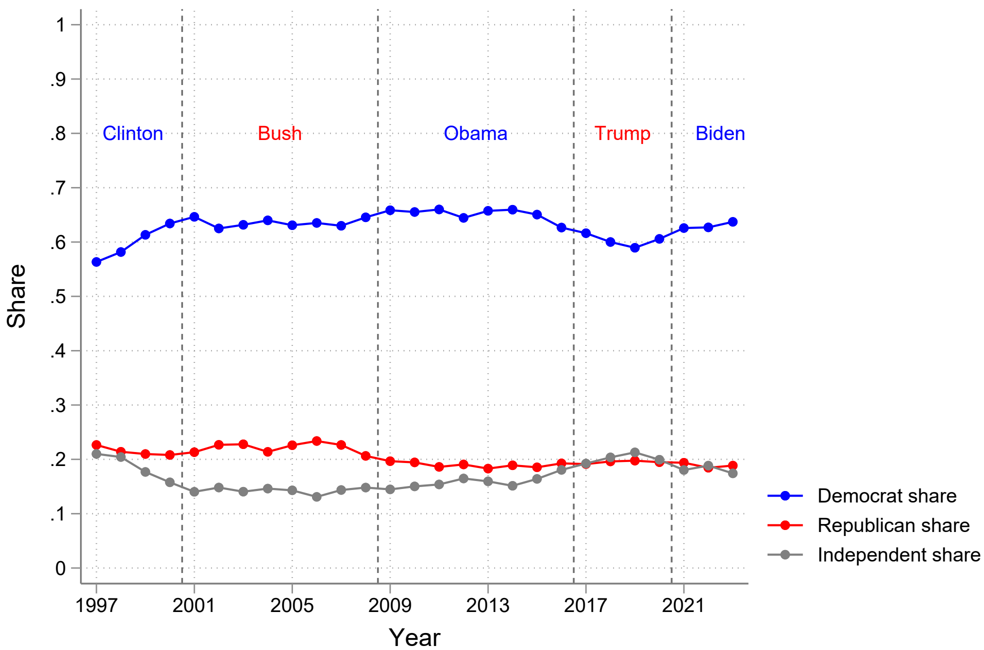
Notes: Figure shows the share of Democrat regulators by department (or major agency) for rules initiated between 1997–2023. AG=Agriculture; CM=Commerce; DHS=Department of Homeland Security; DOD=Department of Defense; DOE=Department of Energy; DOJ=Department of Justice; DOL=Department of Labor; DOT=Department of Transport; EPA=Environmental Protection Agency; HHS=Health & Human Services Department; HUD=Department of Housing and Urban Development; IN=Department of Interior; NRC=Nuclear Regulatory Commission; OPM=Office of Personnel Management; SEC=Securities and Exchange Commission; TREAS=Treasury; VA=Veteran's Affairs. We group departments and agencies with fewer than 500 regulators throughout our sample period 1997–2023 under Other.

Figure 3: Regulator Specialization and Number of Assignments

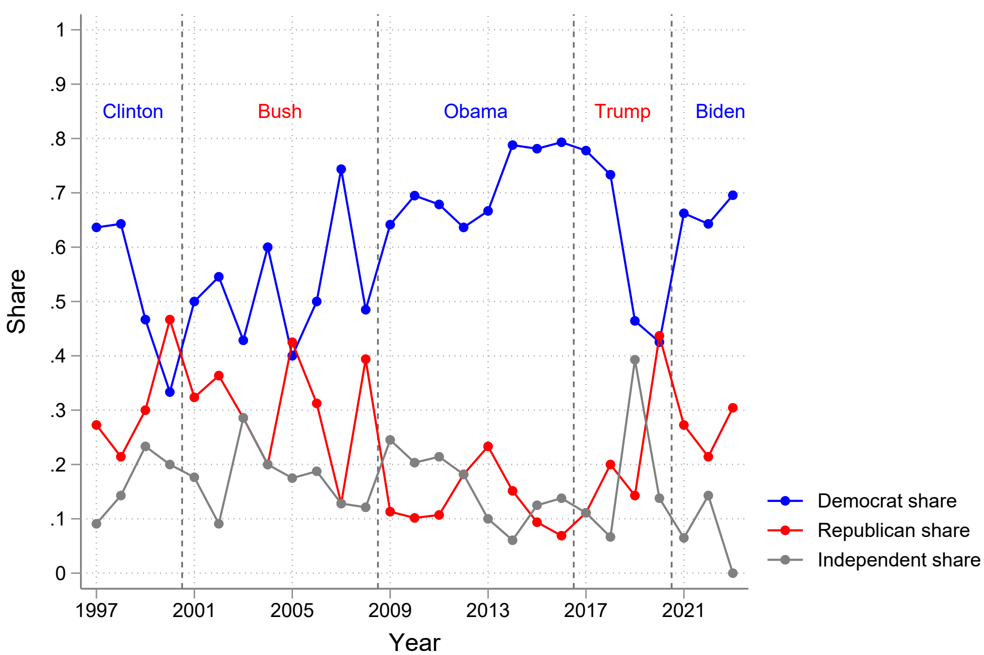


Notes: Figure plots the Herfindahl Index (HHI) for the specialization of regulators to different title-chapter-parts of the Code of Federal Regulation (CFR) as a function of the number of total rules assigned. The solid line shows the *actual* level of specialization – as captured by the HHI – of regulators. The long dashed line shows the counterfactual level of specialization if regulators within the same department/major agency were randomly assigned to rules originating from the same department/major agency. The short dashed line shows the counterfactual level of specialization if regulators were randomly assigned to write rules originating from any department/major agency. The lines are fitted using second-order fractional polynomials (`fpfit`).

Figure 4: Share of Rules by Partisanship of Regulator



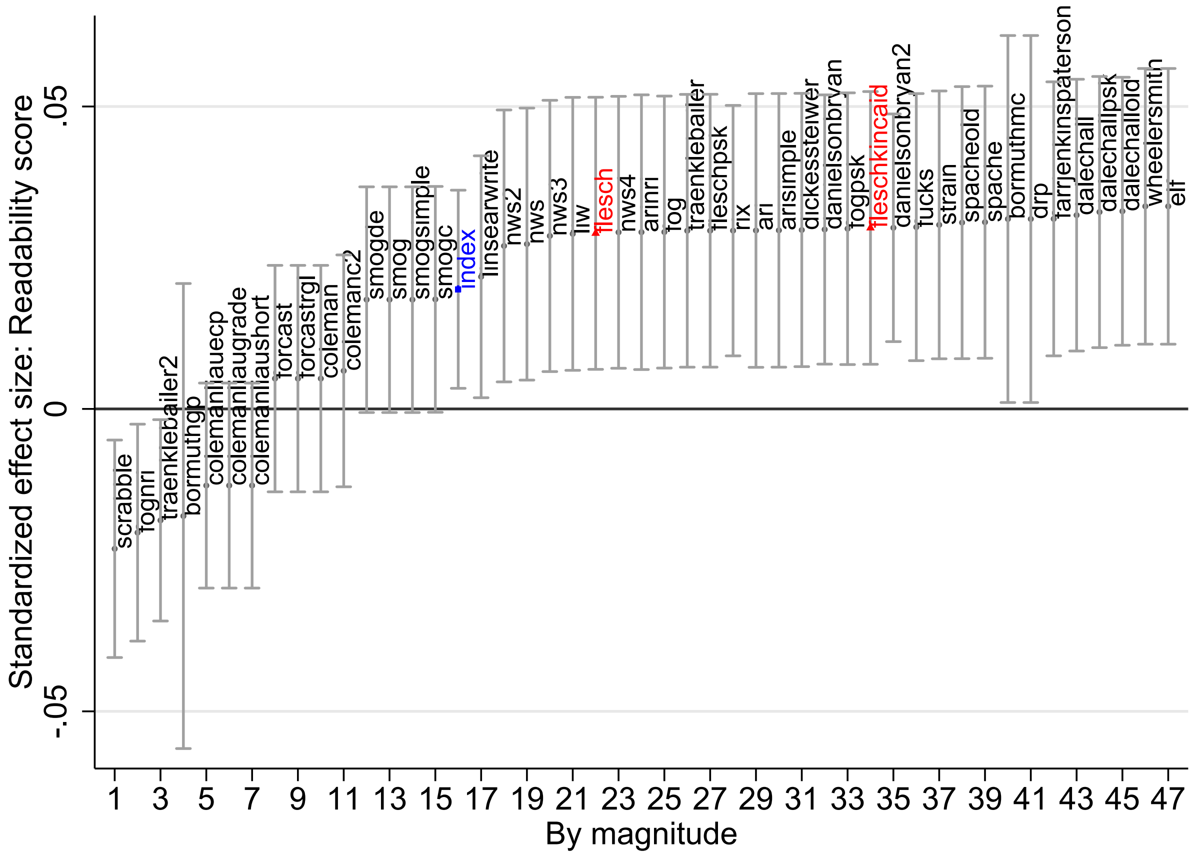
(a) All rules



(b) Newly initiated major rules

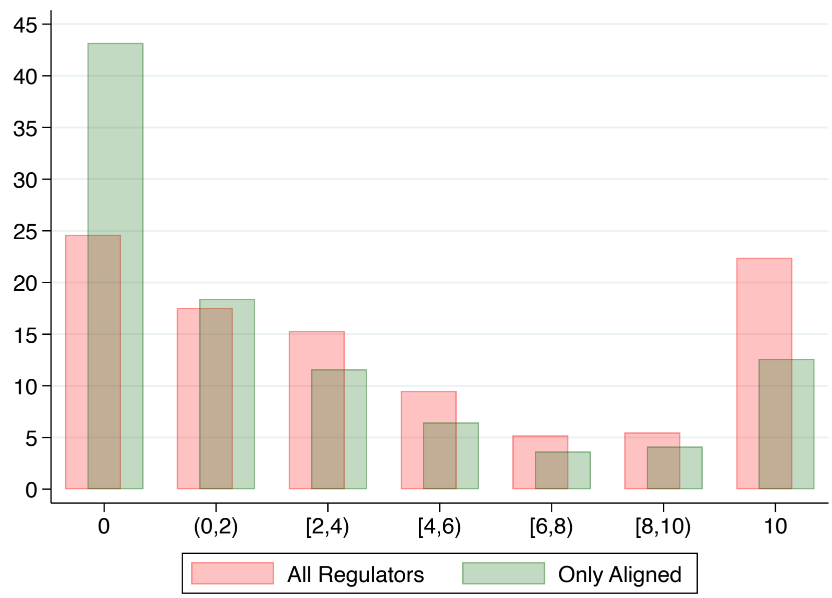
Notes: Figures plot the share of rules by partisanship of the assigned regulator. Panel (a) shows the shares for the stock of all rules that are in progress over time. Panel (b) shows the shares for the flow of newly initiated major rules over time.

Figure 5: Political alignment and Regulatory Text Readability

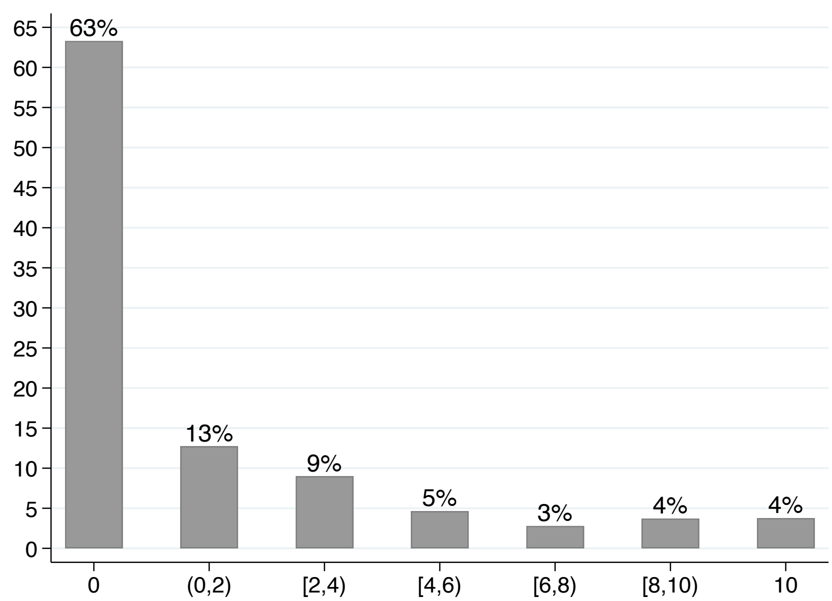


Notes: Figure plots point estimates and their corresponding 95% confidence intervals for the alignment effects based on different readability scores, ordered by magnitude. All point estimates are based on the specification in Table 6 with varying (standardized mean 0 and SD 1) readability scores. The "index" outcome labelled in blue marks the average standardized effect size.

Figure 6: Trade-off Between Political Alignment and Expertise



(a) Distribution of Expertise Scores For Most Expert Regulators



(b) Gap in Expertise Scores if Principals Select Only Aligned Regulators

Notes: Panel (a) focuses on the initial assignment for each rule and plots the distribution of expertise scores across two groups: "All Regulators" are the regulators with the highest expertise scores among those available for each rule; "Only Aligned" are the regulators with the highest expertise scores among those available for each rule and who are aligned with the principal. Panel (b) focuses on the initial assignment for each rule and plots the distribution of gaps in expertise scores across rules, where the gap for each rule is computed as the difference between the expertise score of the most expert among the available regulators and the expertise score of the most expert among the available aligned regulators. Values on the x-axis are bins of the expertise scores (in panel a) and of the gaps in expertise scores (panel b). The y-axis indicates the share of rules that fall in each bin.

Tables

Table 1: Comparing regulators with other bureaucrats in the federal government

	(1)	(2)	(3)	(4)
	Regulators		Other bureaucrats	
	Mean	SD	Mean	SD
Panel A: Demographic characteristics				
Age at entry less than 30	0.486	0.499	0.423	0.499
Age at entry 30-40	0.293	0.454	0.259	0.437
Age at entry 40-50	0.124	0.329	0.173	0.378
Age at entry 50-60	0.073	0.261	0.110	0.312
Age at entry more than 60	0.023	0.149	0.035	0.185
Highest education: college	0.248	0.432	0.232	0.422
Highest education: more than college	0.581	0.493	0.264	0.441
Quarters in federal bureaucracy	74.08	46.54	43.14	44.04
Annual pay (in USD)	51,227.6	43,831.6	40,021.7	34,125.8
Employed in DC	0.659	0.473	0.121	0.326
Political appointment	0.011	0.103	0.004	0.066
Panel B: Voting record characteristics				
Democrat	0.630	0.482	0.490	0.499
Republican	0.206	0.404	0.288	0.453
Independent	0.162	0.369	0.220	0.414
Observations	9,125		1,976,601	

Notes: Comparing mean and SD of regulators and all other bureaucrats of in the OPM dataset. The sample is restricted to all bureaucrats who could be linked to L2.

Table 2: Political alignment and regulator partisanship

Panel A: Democrats	(1)	(2)	(3)	(4)	(5)	(6)
	Share Democrat regulators					
Mean dep. var.	0.630	0.630	0.617	0.605	0.630	0.631
Democrat president	0.019***	0.021***	0.034***	0.133***	0.020***	0.014***
	(0.005)	(0.005)	(0.007)	(0.033)	(0.005)	(0.004)
Year		-0.001	0.001***	0.005**	-0.000	-0.003**
		(0.000)	(0.000)	(0.002)	(0.000)	(0.001)
Rules in sample	All	All	New	New&major	All	All
Agency FEs					✓	
Rule FEs						✓
Observations	109,141	109,141	21,625	854	109,139	105,005
Panel B: Republicans	(1)	(2)	(3)	(4)	(5)	(6)
	Share Republican regulators					
Mean dep. var.	0.204	0.204	0.205	0.241	0.204	0.203
Republican president	0.022***	0.019***	0.021***	0.115***	0.019***	0.009***
	(0.004)	(0.004)	(0.005)	(0.030)	(0.004)	(0.003)
Year		-0.001***	-0.002***	-0.002	-0.002***	0.001
		(0.000)	(0.000)	(0.002)	(0.000)	(0.001)
Rules in sample	All	All	New	New&major	All	All
Agency FEs					✓	
Rule FEs						✓
Observations	109,141	109,141	21,625	854	109,139	105,005

Notes: The unit of observation is a rule-year-month. The sample covers all rules that are active between 1997–2023. Columns 3 restricts the sample to newly initiated rules. Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major (Yes; No; Undetermined), falls under the regulatory flexibility act (RFA) (Yes; No; Undetermined), and its priority level (Economically Significant; Other Significant; Routine and Frequent; Substantive, Nonsignificant; Info./Admin./Other). Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3: Political alignment and rule completion

	(1)	(2)	(3)	(4)	(5)
	Rule completed			Withdrawn	Final
Mean dep. var.	3.7121	3.7121	3.7121	0.8677	2.8444
Share aligned	0.313**	0.386***	0.387***	0.001	0.385***
	(0.125)	(0.126)	(0.126)	(0.077)	(0.102)
Rule FEs	✓	✓	✓	✓	✓
Agency × Year-Month × Duration FEs	✓	✓	✓	✓	✓
Controls × Duration FEs		✓	✓	✓	✓
Experience control			✓	✓	✓
Observations	390,239	390,239	390,239	390,239	390,239

Notes: The unit of observation is a rule-year-month. *Share aligned* captures the share of regulators assigned to a rule in a given rule-year-month that are politically aligned with the president in office at a given time. In columns 1–3, the dependent variable *Rule completed* (scaled by 100) is a dummy that is 1 if the rule was completed in the given rule-year-month. In column 4, *Withdrawn* (scaled by 100) is a dummy that is 1 if the rule was withdrawn in the given rule-year-month; similarly, in column 5, *Final* (scaled by 100) is a dummy that is 1 if the rule was successfully finalized in a given year-month. Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major (Yes; No; Undetermined), falls under the regulatory flexibility act (RFA) (Yes; No; Undetermined), and its priority level (Economically Significant; Other Significant; Routine and Frequent; Substantive, Nonsignificant; Info./Admin./Other). The experience control is a variable capturing the fraction of assigned regulators who have previously worked on the same CFR title-chapter-part. All coefficients are scaled to correspond to percentage point changes associated with a one-unit increase in the respective regressor. Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Political alignment and OIRA review outcomes

	(1)	(2)	(3)	(4)	(5)
	Duration of OIRA review (in days)				Withdrawn/ returned
Mean dep. var.	71.580	71.580	71.580	70.673	0.064
Share aligned	-7.689***	-7.936***	-8.179***	-13.908**	0.020
	(2.795)	(2.749)	(2.734)	(5.433)	(0.022)
Agency × Year-Month FEs	✓	✓	✓	✓	✓
OIRA review Year-Month FEs	✓	✓	✓	✓	✓
Rule-Level Controls		✓	✓		
Experience control			✓	✓	✓
Rule FEs				✓	✓
Observations	6,496	6,496	6,496	4,744	4,742

Notes: The unit of observation is a rule-OIRA review period. *Share aligned* captures the share of regulators assigned to a rule that are politically aligned with the president in office at the time of OIRA review. Rule-level Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major (Yes; No; Undetermined), falls under the regulatory flexibility act (RFA) (Yes; No; Undetermined), and its priority level (Economically Significant; Other Significant; Routine and Frequent; Substantive, Nonsignificant; Info./Admin./Other). The experience control is a variable capturing the fraction of assigned regulators who have previously worked on the same CFR title-chapter-part. Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Political alignment and comment stance

	(1)	(2)	(3)	(4)
	Negative stance			Positive
Mean dep. var.	0.364	0.364	0.364	0.323
Share aligned (initial)	-0.032*	-0.036**	-0.036**	0.039**
	(0.018)	(0.017)	(0.017)	(0.018)
Start year ×month ×Agency FEs	✓	✓	✓	✓
Initial regulator team FEs	✓	✓	✓	✓
Controls		✓	✓	✓
Experience control			✓	✓
Observations	5,297	5,297	5,297	5,297

Notes: The unit of observation is a rule. *Share aligned (initial)* is the share of regulators at rule initiation who are politically aligned with the president. In columns 1–2, the dependent variable *Negative stance* captures the share of comments that are opposing the rule. In column 3, the dependent variable *Positive* captures the share of comments who are supporting the rule. Controls: (log) predicted duration, dummies for whether rule is major (Yes; No; Undetermined), falls under the regulatory flexibility act (RFA) (Yes; No; Undetermined), and its priority level (Economically Significant; Other Significant; Routine and Frequent; Substantive, Nonsignificant; Info./Admin./Other). The experience control is a variable capturing the fraction of assigned regulators who have previously worked on the same CFR title-chapter-part. Robust standard errors. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Political alignment and regulatory text readability

	(1)	(2)	(3)	(4)	(5)
	Text readability			Words/	Syllables/
	Flesch score			sentence	word
Mean dep. var.	-0.008	-0.008	-0.008	57.62	1.74
Share aligned (initial)	0.031**	0.029**	0.029**	-1.451**	0.001
	(0.014)	(0.014)	(0.014)	(0.656)	(0.001)
Initial regulator team FEs	✓	✓	✓	✓	✓
Time × Agency FEs	✓	✓	✓	✓	✓
CFR Title-Part FEs	✓	✓	✓	✓	✓
Controls		✓	✓	✓	✓
Experience controls			✓	✓	✓
Observations	129,260	129,260	129,260	129,260	129,260

Notes: The unit of observation is a rule-CFR title-part. *Share aligned (initial)* is the share of regulators at rule initiation who are politically aligned with the president. In columns 1–3, the dependent variable is the Flesch score. In column 4, the dependent variable is the average words per sentence. In column 5, the dependent variable is the average syllables per word. Controls: (log) predicted duration, dummies for whether rule is major (Yes; No; Undetermined), falls under the regulatory flexibility act (RFA) (Yes; No; Undetermined), and its priority level (Economically Significant; Other Significant; Routine and Frequent; Substantive, Nonsignificant; Info./Admin./Other). The experience control is a variable capturing the fraction of assigned regulators who have previously worked on the same CFR title-chapter-part. Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Political alignment and legal challenge

	(1)	(2)	(3)	(4)
	Legal challenge			
Mean dep. var.	0.25	0.25	0.25	0.21
Share aligned (initial)	-0.068**	-0.084**	-0.087***	-0.275***
	(0.033)	(0.033)	(0.033)	(0.095)
Year × Agency FEs	✓	✓	✓	✓
Controls		✓	✓	✓
Experience control			✓	✓
Initial regulator team FEs				✓
Observations	1,043	1,043	1,043	439

Notes: The unit of observation is a rule. The sample is restricted to major rules. *Share aligned (initial)* is the share of regulators at rule initiation who are politically aligned with the president. The dependent variable *Legal challenge* is a dummy that is 1 if the rule was challenged in federal court, and 0 otherwise. Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major (Yes; No; Undetermined), falls under the regulatory flexibility act (RFA) (Yes; No; Undetermined), and its priority level (Economically Significant; Other Significant; Routine and Frequent; Substantive, Nonsignificant; Info./Admin./Other). The experience control is a variable capturing the fraction of assigned regulators who have previously worked on the same CFR title-chapter-part. Robust standard errors. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

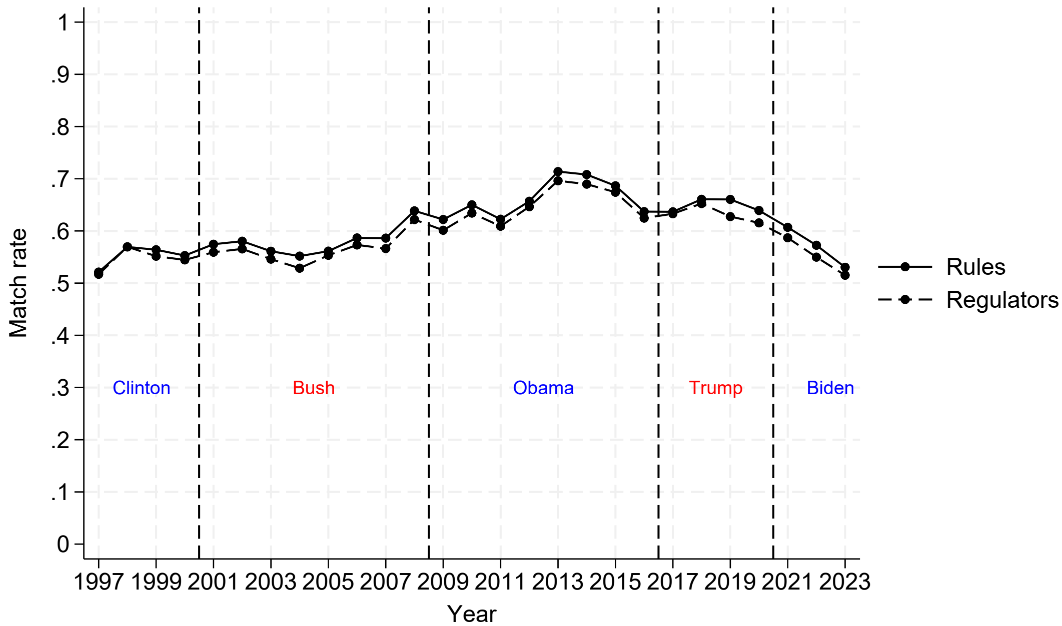
Table 8: Political alignment, expertise match and assignment to rule

	(1)	(2)	(3)	(4)
	Assigned to rule ($\times$ 100)			
Mean dep. var. no aligned and no expert	0.358	0.358	0.358	0.358
Expertise match	6.766***	6.664***	7.555***	7.387***
	(0.074)	(0.072)	(0.077)	(0.090)
Aligned	0.043***	0.047***	0.014	-0.018
	(0.013)	(0.013)	(0.016)	(0.014)
Expertise match $\times$ Aligned				0.407***
				(0.121)
Rule FEs	✓	✓	✓	✓
Experience FEs		✓	✓	✓
Regulator FEs			✓	✓
Observations	2,483,196	2,483,196	2,483,152	2,483,152

Notes: The unit of observation is a rule-regulator. For every rule, the set of regulators are restricted to "potential regulators"), defined as those serving in the same department of the rule's origin department and observed writing rules both before and after the rule of interest. Aligned is a dummy that is 1 if the regulator is aligned with the president at the time the rule is initiated, and 0 otherwise. Expertise match is a dummy that is 1 if the regulator has ever written a rule covering the same Code of Federal Regulation's title-chapter-part that the rule of interest plans to modify, and 0 otherwise. Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix

Figure A1: Matching rate over time



Notes: Figure shows the fraction of rules and regulators who could be matched to the voter registration data (L2) over time. The solid line shows the fraction of rules for whom at least one regulator could be successfully matched to L2. The dashed line shows the fraction of regulators who could be matched to L2.

Table A1: Summary of sample restrictions

(1) Step	(2) Sample restriction	(3) # rules	(4) # observations
Panel A: Rule-level			
A.1.	Raw data (Unified Agenda)		43,366
A.2.	Drop duplicate/merged RINs		42,550
A.3.	Drop RINs without regulator information		41,990
A.4.	Drop RINs started before 1997		35,657
A.5.	Matched to L2		24,027
Panel B: Rule-year-month level			
B.1.	Exclude from A.5. RINs observed in single UA	18,605	516,597
B.2.	Restrict to completed RINs	18,071	463,464
B.3.	Drop missing data, singleton FE cells	15,834	390,239
Panel C: Rule-OIRA-review level			
C.1.	Raw data (OIRA)	9,458	14,914
C.2.	Merge with Sample A.5 RINs	4,216	6,945
C.3.	Drop missing data, singleton FE cells	3,853	6,496
Panel D: Rule-comment level			
D.1.	Raw data (comments)	n/a	13,419,102
D.2.	Dropping invalid data (e.g., unreadable)	n/a	12,785,789
D.3.	Linked to Unified Agenda RINs	10,877	11,370,159
D.3.	Impose Sample A.5. restriction	8,036	9,326,368
	(# unique NPRMs in parenthesis)		(10,966)
D.4.	Drop missing data, singleton FE cells	3,835	6,403,264
	(# unique NPRMs in parenthesis)		(5,297)
Panel E: Rule-section level			
E.1.	Raw data (CFR)	n/a	427,055
E.2.	Linked to Unified Agenda RINs	20,249	251,585
E.3.	Impose Sample A.5. restriction	13,602	177,366
E.4.	Drop missing data, singleton FE cells	10,837	129,260
Panel F: Rule-level (legal challenge)			
F.1.	Raw data (Institute for Policy Integrity)		1,863
F.2.	Merge with Sample A.5 RINs		1,291
F.3	Drop missing data, singleton FE cells		1,043

Notes: Table summarizes the sample restrictions imposed beginning with the raw Unified Agenda (UA) data to arrive at the final analysis sample of rules. Column 3 shows the number of unique rules; column 4 shows the number of observations in respective unit (see panel title). In Panel D, the unit of observation is the comment but the regression analysis aggregates comments at the comment-process (NPRM) level.

Table A2: Baseline characteristics of matched vs. unmatched sample

	(1) Mean unmatched	(2) Raw mean matched-unmatched	(3) Obs.
Panel A: Rule-level			
Predicted delay (log)	5.315	-0.034***	35,657
		(0.013)	
Significant rule	0.025	0.002***	35,657
		(0.002)	
Major rule	0.023	0.014***	35,657
		(0.003)	
Under RFA	0.060	0.002***	35,657
		(0.003)	
Panel B: CFR section-level			
Flesch score	0.018	-0.032	178,807
		(0.020)	
Avg. words/sentence	55.41	1.653*	178,807
		(0.854)	
Avg. syllables/word	1.74	-0.001	178,807
		(0.003)	
Word count	1357.47	14.790	178,807
		(45.759)	

Notes: Descriptive statistics for rule and CFR characteristics by rules with any matched regulator vs. no matched regulator. Column 1 shows the mean; column 2 reports the raw difference between aligned vs. misaligned rules. Flesch score is standardized, with higher scores indicating greater readability. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A3: Political alignment and baseline characteristics

	(1) Mean misaligned	(2) Mean diff aligned-misaligned Raw	(3) Conditional	(4) Obs.
Panel A: Rule-level				
Predicted delay (log)	5.27	0.006	-0.023	24,027
		(0.016)	(0.019)	
Significant rule	0.038	0.009***	-0.000	24,027
		(0.003)	(0.004)	
Major rule	0.034	0.011***	0.003	24,027
		(0.002)	(0.004)	
Under RFA	0.077	0.005	0.002	24,027
		(0.003)	(0.006)	
Joint significance (p-value)		0.000***	0.614	
Panel B: CFR section-level				
Flesch score	0.003	0.018	0.038	131,666
		(0.019)	(0.034)	
Avg. words/sentence	57.39	-0.756	-2.406	131,666
		(0.846)	(1.588)	
Avg. syllables/word	1.738	0.007**	0.008**	131,666
		(0.003)	(0.004)	
Word count	1414.52	-50.009	70.589	131,666
		(36.194)	(115.185)	
Joint significance (p-value)		0.009***	0.039**	

Notes: Descriptive statistics for rule and CFR characteristics by political alignment at time of rule initiation. Column 1 shows the mean; columns 2–3 report the difference between aligned vs. misaligned rules, with column 2 reporting the raw difference and column 3 reporting the difference after partialing out the set of FEs. For the rule-level characteristics, the fixed effects include regulator team FEs and rule initiation year × month × agency FEs. For CFR-level characteristics, the additional fixed effects include the CFR-title-part FEs and CFR publication year × month × agency FEs (see description in Equation 4). Flesch score is standardized, with higher scores indicating greater readability. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A4: Political alignment and rule completion – robustness and heterogeneity

	(1)	(2)	(3)	(4)	(5)
	Rule completed				
Mean dep. var.	3.7121	3.8325	3.7695	3.8644	3.9750
Share aligned	0.387***	0.395***	0.402***	0.302	0.462
	(0.126)	(0.142)	(0.140)	(0.238)	(0.323)
Sample	All	Fully mis/ aligned	Single regulator	Democrat vs. Indep.	Republican vs. Indep.
Rule FEs	✓	✓	✓	✓	✓
Agency × Year-Month × Duration FEs	✓	✓	✓	✓	✓
Controls × Duration FEs	✓	✓	✓	✓	✓
Experience control	✓	✓	✓	✓	✓
Observations	390,239	331,483	327,923	260,971	106,491

Notes: The unit of observation is a rule-year-month. *Share aligned* captures the share of regulators assigned to a rule based on the party composition at a given time. The dependent variable *Rule completed* (scaled by 100) is a dummy that is 1 if the rule was completed in the given rule-year-month. Column 1 shows the baseline estimates for all rules; column 2 restricts the sample to rules that were initiated under full alignment or misalignment; column 3 restricts the sample to rules initiated with a single regulator assigned; columns 4–5 break down the sample by rules initiated under Democrat (column 4) and Republican (column 5) presidents. Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major (Yes; No; Undetermined), falls under the regulatory flexibility act (RFA) (Yes; No; Undetermined), and its priority level (Economically Significant; Other Significant; Routine and Frequent; Substantive, Nonsignificant; Info./Admin./Other). The experience control is a variable capturing the fraction of assigned regulators who have previously worked on the same CFR title-chapter-part. Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: Political alignment and rule completion – based on initial regulator composition

	(1)	(2)	(3)	(4)
	Completed		Final	
Mean dep. var.	3.8261	3.8261	2.9706	2.9706
Share aligned	0.400***		0.429***	
	(0.138)		(0.114)	
Share aligned (initial)		0.344**		0.402***
		(0.158)		(0.123)
Rule FEs	✓	✓	✓	✓
Agency × Year-Month × Duration FEs	✓	✓	✓	✓
Controls × Duration FEs	✓	✓	✓	✓
Experience control	✓	✓	✓	✓
Observations	342,359	342,359	342,359	342,359

Notes: The unit of observation is a rule-year-month. *Share aligned* captures the share of regulators assigned to a rule based on the party composition at a given time. *Share aligned (initial)* captures the share of regulators assigned to a rule based on the party composition at time of rule initiation. The dependent variable *Completed* (scaled by 100) is a dummy that is 1 if the rule was completed in the given rule-year-month. *Final* (scaled by 100) is a dummy that is 1 if the rule was completed as a final rule (i.e., not withdrawn) in a given rule-year-month. Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major (Yes; No; Undetermined), falls under the regulatory flexibility act (RFA) (Yes; No; Undetermined), and its priority level (Economically Significant; Other Significant; Routine and Frequent; Substantive, Nonsignificant; Info./Admin./Other). The experience control is a variable capturing the fraction of assigned regulators who have previously worked on the same CFR title-chapter-part. Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6: Political alignment and OIRA review outcomes – robustness and heterogeneity

	(1)	(2)	(3)	(4)	(5)
	Duration of OIRA review (days)				
Mean dep. var.	70.67	70.36	70.48	68.62	69.99
Share aligned	-13.908**	-13.856**	-12.985**	-32.879***	0.443
	(5.433)	(5.458)	(6.024)	(10.828)	(13.097)
Sample	All	Fully mis/ aligned	Single regulator	Democrat vs. Indep.	Republican vs. Indep.
Rule FEs	✓	✓	✓	✓	✓
OIRA review Year-Month FEs	✓	✓	✓	✓	✓
Agency × Year-Month FEs	✓	✓	✓	✓	✓
Controls × Duration FEs	✓	✓	✓	✓	✓
Experience control	✓	✓	✓	✓	✓
Observations	4,744	4,567	3,779	3,167	1,192

Notes: The unit of observation is a rule-year-month. *Share aligned* captures the share of regulators assigned to a rule based on the party composition at a given time. The dependent variable is the number of days taken to complete the OIRA review. Column 1 shows the baseline estimates for all rules; column 2 restricts the sample to rules that were initiated under full alignment or misalignment; column 3 restricts the sample to rules initiated with a single regulator assigned; in column 4, the sample is restricted to rules assigned to Democrats and Independents; in column 5, the sample is restricted to rules assigned to Republicans and Independents. Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major (Yes; No; Undetermined), falls under the regulatory flexibility act (RFA) (Yes; No; Undetermined), and its priority level (Economically Significant; Other Significant; Routine and Frequent; Substantive, Nonsignificant; Info./Admin./Other). The experience control is a variable capturing the fraction of assigned regulators who have previously worked on the same CFR title-chapter-part. Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7: Political alignment and number of comments – robustness and heterogeneity

	(1)	(2)	(3)	(4)	(5)
			Negative stance		
Mean dep. var.	0.363	0.363	0.363	0.374	0.347
Share aligned (initial)	-0.038**	-0.038**	-0.038**	-0.059	-0.050***
	(0.015)	(0.015)	(0.015)	(0.039)	(0.018)
Sample	All	Fully mis/ aligned	Single regulator	Democrat vs. Indep.	Republican vs. Indep.
Initial regulator team FEs	✓	✓	✓	✓	✓
Time × Agency FEs	✓	✓	✓	✓	✓
CFR Title-Part FEs	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Experience controls	✓	✓	✓	✓	✓
Observations	6,226	6,101	6,101	4,467	4,066

Notes: The unit of observation is a rule. *Share aligned (initial)* captures the share of regulators assigned to a rule based on the party composition at a given time. The dependent variable captures the share of comments that are opposing the rule. Column 1 shows the baseline estimates for all rules; column 2 restricts the sample to rules that were initiated under full alignment or misalignment; column 3 restricts the sample to rules initiated with a single regulator assigned; in column 4, the sample is restricted to rules assigned to Democrats or Independents; in column 5, the sample is restricted to rules assigned to Republicans or Independents. Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major (Yes; No; Undetermined), falls under the regulatory flexibility act (RFA) (Yes; No; Undetermined), and its priority level (Economically Significant; Other Significant; Routine and Frequent; Substantive, Nonsignificant; Info./Admin./Other). The experience control is a variable capturing the fraction of assigned regulators who have previously worked on the same CFR title-chapter-part. Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8: Political alignment and number of comments

	(1)	(2)	(3)	(4)
	Any	# comments above		Log(No.
	comment	Median	90%	comments
Mean dep. var.	0.678	0.518	0.100	3.076
Share aligned (initial)	-0.010	-0.006	-0.000	0.087
	(0.018)	(0.023)	(0.013)	(0.113)
Initial regulator team FEs	✓	✓	✓	✓
Time × Agency FEs	✓	✓	✓	✓
CFR Title-Part FEs	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Experience controls	✓	✓	✓	✓
Observations	9,611	9,611	9,611	6,226

Notes: The unit of observation is a rule. *Share aligned (initial)* is the share of regulators at rule initiation who are politically aligned with the president. Any comment (column 1) is a dummy that is 1 if at least a single comment was submitted to the rule's NPRM. The dependent variables in columns 2–3 are dummies for whether the number of comments are above median or among the top 10%. In column 4, the dependent variable is the log(number of comments), restricting the sample to only rules with at least a single comment. Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major (Yes; No; Undetermined), falls under the regulatory flexibility act (RFA) (Yes; No; Undetermined), and its priority level (Economically Significant; Other Significant; Routine and Frequent; Substantive, Nonsignificant; Info./Admin./Other). The experience control is a variable capturing the fraction of assigned regulators who have previously worked on the same CFR title-chapter-part. Robust standard errors. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9: Political alignment and regulatory text length

	(1)	(2)	(3)	(4)
	Number	Section		Number
	words	Added	Removed	words
Mean dep. var.	1179	0.235	0.038	1473
Share aligned (initial)	-41.729	0.010	0.002	-51.008*
	(33.476)	(0.013)	(0.006)	(28.202)
Initial regulator team FEs	✓	✓	✓	✓
Time × Agency FEs	✓	✓	✓	✓
CFR Title-Part FEs	✓	✓	✓	✓
Controls	✓	✓	✓	✓
Experience controls	✓	✓	✓	✓
Observations	178,645	178,645	178,645	129,260

Notes: The unit of observation is a rule-CFR title-part. *Share aligned (initial)* is the share of regulators at rule initiation who are politically aligned with the president. In columns 1 and 4, the dependent variable is the number of words. In column 2, the dependent variable is a dummy that is 1 if a new section was added to the CFR; similarly, in column 3, the dependent variable is a dummy that is 1 if a section was removed from the CFR. Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major (Yes; No; Undetermined), falls under the regulatory flexibility act (RFA) (Yes; No; Undetermined), and its priority level (Economically Significant; Other Significant; Routine and Frequent; Substantive, Nonsignificant; Info./Admin./Other). The experience control is a variable capturing the fraction of assigned regulators who have previously worked on the same CFR title-chapter-part. Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A10: Political alignment and regulatory text readability - robustness and heterogeneity

	(1)	(2)	(3)	(4)	(5)
	Text readability – Flesch score				
Mean dep. var.	-0.008	-0.008	-0.009	0.001	-0.002
Share aligned (initial)	0.029**	0.029**	0.028**	0.036	0.113
	(0.014)	(0.014)	(0.014)	(0.028)	(0.077)
Sample	All	Fully mis/ aligned	Single regulator	Democrat vs. Indep.	Republican vs. Indep.
Initial regulator team FEs	✓	✓	✓	✓	✓
Time × Agency FEs	✓	✓	✓	✓	✓
CFR Title-Part FEs	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Experience controls	✓	✓	✓	✓	✓
Observations	129,260	125,139	108,659	86,507	41,193

Notes: The unit of observation is a rule-CFR title-part. *Share aligned (initial)* is the share of regulators at rule initiation who are politically aligned with the president. The dependent variable is the Flesch score. Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major (Yes; No; Undetermined), falls under the regulatory flexibility act (RFA) (Yes; No; Undetermined), and its priority level (Economically Significant; Other Significant; Routine and Frequent; Substantive, Nonsignificant; Info./Admin./Other). The experience control is a variable capturing the fraction of assigned regulators who have previously worked on the same CFR title-chapter-part. Column 1 is the baseline; column 2 restricts the sample to rules assigned to fully aligned or fully misaligned regulators; column 3 restricts the sample to rules assigned to a single regulator; in column 4, the sample is restricted to rules assigned to Democrat or Independent regulators; in column 5, the sample is restricted to rules assigned to Republican or Independent regulators. Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A11: Robustness: Political alignment and regulatory text – winsorizing

	(1)	(2)	(3)	(4)	(5)
		Winsorization (two-tailed)			
Winsorizing	None	0.1%	0.5%	1%	2.5%
Flesch score					
Share aligned (initial)	2.317**	1.763**	0.029**	1.352**	0.998**
	(1.109)	(0.790)	(0.014)	(0.612)	(0.488)
Flesch-Kincaid score					
Share aligned (initial)	0.903**	0.677**	0.030**	0.536**	0.383**
	(0.424)	(0.298)	(0.014)	(0.228)	(0.180)
Avg. words/sentence					
Share aligned (initial)	-2.334**	-1.737**	-1.451**	-1.398**	-0.997**
	(1.086)	(0.758)	(0.657)	(0.577)	(0.458)
Avg. syllables/word					
Share aligned (initial)	0.001	0.001	0.001	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Post-rule word count					
Share aligned (initial)	-472.604*	-212.985**	-51.008*	-36.706	-26.448
	(245.338)	(95.260)	(28.202)	(25.744)	(18.396)
Regulator team FEs	✓	✓	✓	✓	✓
Start year ×month ×Agency FEs	✓	✓	✓	✓	✓
End year ×month ×Agency FEs	✓	✓	✓	✓	✓
Pre-rule (baseline) word count	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Observations	129,260	129,260	129,260	129,260	129,260

Notes: The unit of observation is a rule-CFR title-chapter-part. Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major (Yes; No; Undetermined), falls under the regulatory flexibility act (RFA) (Yes; No; Undetermined), and its priority level (Economically Significant; Other Significant; Routine and Frequent; Substantive, Nonsignificant; Info./Admin./Other). Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A12: Political alignment and and legal challenge – robustness and heterogeneity

	(1)	(2)	(3)	(4)	(5)
			Legal challenge		
Mean dep. var.	0.214	0.218	0.217	0.237	0.185
Share aligned (initial)	-0.275***	-0.275***	-0.271***	-0.474**	-0.841***
	(0.095)	(0.095)	(0.096)	(0.218)	(0.225)
Sample	All	Fully mis/ aligned	Single regulator	Democrat vs. Indep.	Republican vs. Indep.
Year × Agency FEs	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓
Experience control	✓	✓	✓	✓	✓
Initial regulator team FEs	✓	✓	✓	✓	✓
Observations	439	430	423	286	151

Notes: The unit of observation is a rule. The sample is restricted to major rules. *Share aligned (initial)* is the share of regulators at rule initiation who are politically aligned with the president. The dependent variable *Legal challenge* is a dummy that is 1 if the rule was challenged in federal court, and 0 otherwise. Controls: (log) predicted duration, number of regulator FEs, dummies for whether rule is major (Yes; No; Undetermined), falls under the regulatory flexibility act (RFA) (Yes; No; Undetermined), and its priority level (Economically Significant; Other Significant; Routine and Frequent; Substantive, Nonsignificant; Info./Admin./Other). The experience control is a variable capturing the fraction of assigned regulators who have previously worked on the same CFR title-chapter-part. Column 1 is the baseline; in column 2, the sample is restricted to rules that are fully aligned or fully misaligned; in column 3, the sample is restricted to rules assigned a single regulator; in column 4, the sample is restricted to Democrats or Independents; in column 5, the sample is restricted to Republicans or Independents. Robust standard errors. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A13: Political alignment, expertise match and assignment to rule (all rule-year-months observations)

	(1)	(2)	(3)	(4)
		Assigned to rule (× 100)		
Mean dep. var. no aligned and no expert	0.314	0.314	0.314	0.314
Expertise match	6.087***	5.863***	6.852***	6.630***
	(0.028)	(0.028)	(0.031)	(0.035)
Aligned	0.030***	0.031***	0.005	-0.044***
	(0.005)	(0.005)	(0.007)	(0.006)
Expertise match × Aligned				0.549***
				(0.048)
Rule FEs	✓	✓	✓	✓
Experience FEs		✓	✓	✓
Regulator FEs				✓
Observations	13,618,317	13,618,317	13,618,305	13,618,305

Notes: The unit of observation is a rule-year-month-regulator. For every rule-year-month, the set of regulators are restricted to "potential regulators"), defined as those serving in the same department of the rule's origin department and observed writing rules both before and after the rule of interest. Aligned is a dummy that is 1 if the regulator is aligned with the president at the time the rule is initiated, and 0 otherwise. Expertise match is a dummy that is 1 if the regulator has ever written a rule covering the same Code of Federal Regulation's title-chapter-parts that the rule of interest plans to modify, and 0 otherwise. Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A14: Political alignment, expertise match and assignment to rule (continuous measure of expertise match)

	(1)	(2)	(3)	(4)
	Assigned to rule (× 100)			
Mean dep. var. no aligned and no expert	0.358	0.358	0.358	0.358
Expertise match	7.795***	7.665***	8.769***	8.522***
	(0.087)	(0.084)	(0.088)	(0.104)
Aligned	0.044***	0.047***	0.010	-0.033**
	(0.013)	(0.013)	(0.016)	(0.014)
Expertise match × Aligned				0.603***
				(0.141)
Rule FEs	✓	✓	✓	✓
Experience FEs		✓	✓	✓
Regulator FEs				✓
Observations	2,483,196	2,483,196	2,483,152	2,483,152

Notes: The unit of observation is a rule-regulator. For every rule, the set of regulators are restricted to "potential regulators"), defined as those serving in the same department of the rule's origin department and observed writing rules both before and after the rule of interest. Aligned is a dummy that is 1 if the regulator is aligned with the president at the time the rule is initiated, and 0 otherwise. Expertise match is the share of Code of Federal Regulation's title-chapter-parts that the rule plans to modify on which the regulator has previous experience. Standard errors are clustered at the rule-level. Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Online Appendix

A Data on Rulemaking

In this section, we describe the four sources of rulemaking data we use throughout the analysis and how we link them together. First, the Unified Agenda of Federal Regulatory and Deregulatory Actions (UA) defines our sample of rulemaking processes. Second, the Federal Register (FR) represents the flow of regulations, where regulatory actions (e.g., proposed and final rules) are published and announced. Third, the Code of Federal Regulations (CFR) represents the stock of rulemaking, including all effective regulatory provisions. Fourth, comments data for regulatory actions is obtained from Regulations.gov, the official online portal where agencies deposit the comments received during the notice-and-comment process.

A1 Unified Agenda

The Unified Agenda (UA) describes the regulatory processes that agencies are developing or have completed. The UA is published twice a year, in the spring and fall. A Regulation Identifier Number (RIN) is assigned to each regulatory process, allowing us to track the progress of the rulemaking process and the adoption of regulatory actions over time. Figure A.1 shows how a regulatory process is carried over through several issues of the UA. The proposed rule associated with RIN 2050-AG83 first appears in the UA in the Spring issue of 2015, while the action is reported as completed three years later, in the Spring issue of 2018.

Figure A.1: Example of RIN progress through multiple sessions of the Unified Agenda.

Agency	Agenda Stage of Rulemaking	Title	Publication	RIN
EPA/SWER	Proposed Rule Stage	Non-Hazardous Secondary Materials--Additions to List of Categorical Non-Waste Fuels; Other Treated Woods	Spring 2015	2050-AG83
EPA/SWER	Long-Term Actions	Non-Hazardous Secondary Materials--Additions to List of Categorical Non-Waste Fuels; Other Treated Woods	Fall 2015	2050-AG83
EPA/OLEM	Proposed Rule Stage	Non-Hazardous Secondary Materials - Additions to List of Categorical Non-Waste Fuels; Other Treated Railroad Ties and Used Oil	Spring 2016	2050-AG83
EPA/OLEM	Proposed Rule Stage	Non-Hazardous Secondary Materials -- Additions to List of Categorical Non-Waste Fuels; Other Treated Railroad Ties and Used Oil	Fall 2016	2050-AG83
EPA/OLEM	Final Rule Stage	Non-Hazardous Secondary Materials--Additions to List of Categorical Non-Waste Fuels; Other Treated Railroad Ties	Spring 2017	2050-AG83
EPA/OLEM	Final Rule Stage	Non-Hazardous Secondary Materials--Additions to List of Categorical Non-Waste Fuels; Other Treated Railroad Ties	Fall 2017	2050-AG83
EPA/OLEM	Completed Actions	Non-Hazardous Secondary Materials--Additions to List of Categorical Non-Waste Fuels; Other Treated Railroad Ties	Spring 2018	2050-AG83

Notes: UA records for RIN 2050-AG83 as reported on the Unified Agenda website.

Each RIN-UA issue pair captures the progress of the rulemaking process. Two of them are displayed Figure A.2 below. Panel A shows the status of the process reported in the Spring issue of 2015, whereas Panel B shows the status of the regulatory process in its latest issue in 2018.

Figure A.2: Example of RIN across two UA issues.

A) Spring 2015 Issue

EPA/SWER **RIN:** 2050-AG83 **Publication ID:** Spring 2015

Title: ●Non-Hazardous Secondary Materials--Additions to List of Categorical Non-Waste Fuels; Other Treated Woods

Abstract:

In the 2013 Non-Hazardous Secondary Materials (NHSM) final rule, the EPA established a rulemaking process for categorical determinations for adding NHSMs as non-waste fuels. Persons requesting rulemakings for adding NHSMs to the list of categorical non-wastes will have to demonstrate how the NHSMs successfully meet the criteria listed in 40 CFR 241.4(b)(5). The Treated Wood Council has submitted a petition for various types of treated wood to be added as categorical non-waste fuels.

Agency: Environmental Protection Agency(EPA)
Priority: Substantive, Nonsignificant
RIN Status: First time published in the Unified Agenda
Agenda Stage of Rulemaking: Proposed Rule Stage
Major: No
Unfunded Mandates: No
CFR Citation: 40 CFR 241
Legal Authority: 42 U.S.C. 6903 42 U.S.C. 6912 42 U.S.C. 7429
Legal Deadline: None
Timetable:

Action	Date	FR Cite
NPRM	07/00/2015	

Regulatory Flexibility Analysis Required: No
Government Levels Affected: None
Small Entities Affected: No
Federalism: No
Included in the Regulatory Plan: No

B) Spring 2018 Issue

EPA/OLEM **RIN:** 2050-AG83 **Publication ID:** Spring 2018

Title: Non-Hazardous Secondary Materials--Additions to List of Categorical Non-Waste Fuels; Other Treated Railroad Ties

Abstract:

The non-hazardous secondary material (NHSM) regulations under the Resource Conservation and Recovery Act (RCRA) identify which NHSMs are, or are not, solid wastes when burned in combustion units as ingredients and fuels. Under 40 CFR 241.4(b), persons can petition the EPA to list additional NHSMs as categorical non-waste fuels.

The Agency received a petition from the Treated Wood Council in April 2013 requesting that nonhazardous treated wood biomass be categorically listed as non-waste fuels. In August 2015, the Treated Wood Council requested that the Agency move forward on a categorical non-waste listing for a subset of materials that were identified in the April 2013 petition; specifically, other treated railroad ties that are treated with the preservatives creosote-borate, copper naphthenate, and copper naphthenate-borate. On February 7, 2018, EPA issued a final rule that added these other treated railroad ties to the categorical non-waste fuel list.

Agency: Environmental Protection Agency(EPA)
Priority: Other Significant
RIN Status: Previously published in the Unified Agenda
Agenda Stage of Rulemaking: Completed Actions
Major: No
Unfunded Mandates: No
EO 13771 Designation: Deregulatory
CFR Citation: 40 CFR 241
Legal Authority: 42 U.S.C. 6903 42 U.S.C. 6912 42 U.S.C. 7429
Legal Deadline: None
Timetable:

Action	Date	FR Cite
NPRM	11/01/2016	81 FR 75781
Final Rule	02/07/2018	83 FR 5317
Final Action Effective	02/07/2018	

Additional Information: Docket # EPA-HQ-OLEM-2016-0248
Regulatory Flexibility Analysis Required: No
Government Levels Affected: None
Small Entities Affected: No
Federalism: No
Included in the Regulatory Plan: No

Notes: UA entry across issues for RIN 2050-AG83 as reported on the Unified Agenda website.

The information reported in each issue of the UA retains the same structure. In addition to self-explanatory details such as the title, abstract, RIN, stage of rulemaking, and agency, the UA reports rule-specific characteristics: whether the rule is considered "Major" (i.e., is expected to have a significant economic impact), the title and part of the Code of Federal Regulations that the rule proposes to amend, the statutory authority granting the rulemaking agency the power to issue a rule on this matter, whether the rule is subject to a legal deadline, the priority status of the rule (whether it is considered significant or not), unfunded mandates (i.e., imposes increased costs on non-federal government entities), whether the rule falls under the Regulatory Flexibility Act (RFA), whether the rule is included in the regulatory plan, and whether it affects government levels, federalism, or small entities.

Importantly, the UA provides information on the names and contact details of the bureaucrats assigned to every action throughout the regulatory process. For RIN 2050-AG83, for example, each of the seven issues of the UA from 2015 to 2018 lists the same two bureaucrats, whose contact information is shown in Figure A.3 as it appears in the UA.

Figure A.3: Example of bureaucrats assigned to RIN 2050-AG83.

Agency Contact:
Jesse Miller
Environmental Protection Agency
Solid Waste and Emergency Response
1200 Pennsylvania Avenue NW, Mail Code 5304T,
Washington, DC 20460
Phone:202 566-0562
Email: miller.jesse@epa.gov

George Faison
Environmental Protection Agency
Solid Waste and Emergency Response
1200 Pennsylvania Avenue NW, Mail Code 5303P,
Washington, DC 20460
Phone:703 305-7652
Email: faison.george@epa.gov

Notes: Contact information of bureaucrats assigned to regulatory actions as reported on the Unified Agenda website.

Finally, each record in the UA includes a timetable of the regulatory process until the publication of that issue, presented in tabular format, where each row reports a single action adopted over time along with its respective date of adoption. Such actions can include, for example, the Notice of Proposed Rulemaking (NPRM) or the final rule. In most cases, actions are documented in the Federal Register and referenced by an FR Cite that identifies the Volume (83, for the final rule) and the page number (5317). Figure A.4 shows the initial information regarding the publication of the final rule in the Federal Register. The heading of the page reports the volume and page of the Federal Register. The text of the entry presents some of the same information already described above and reported in the UA. The Federal Register also includes the full text of the rule, which for RIN 2050-AG83 spans 24 pages.

Figure A.4: Federal Register entry for the final rule of RIN 2050-AG83.

Federal Register / Vol. 83, No. 26 / Wednesday, February 7, 2018 / Rules and Regulations **5317**

ENVIRONMENTAL PROTECTION AGENCY

40 CFR Part 241

[EPA–HQ–OLEM–2016–0248; FRL–9969–80–OLEM]

RIN 2050–AG83

Additions to List of Categorical Non-Waste Fuels: Other Treated Railroad Ties

AGENCY: Environmental Protection Agency (EPA).

ACTION: Final rule.

Notes: Publication of the final rule from RIN 2050-AG83 in the Federal Register, volume 83, page 5317.

We download the universe of rulemaking processes published in the UA directly from the UA website, which includes an XML file for each UA issue.[36] Each element of the XML file is a RIN-UA issue observation, containing all the information we described and displayed above. In total, we observe 43,366 regulatory processes (RINs). After applying the sample restrictions described in Table A2 (A.1-A.4) we obtain 35,657 unique regulatory processes. 34,414 RINs include regulatory actions with a valid FR cite, for a total of 71,185 unique regulatory actions.

To identify the changes that final rules make to the CFR and to access stakeholder comments on proposed rules, we augment the UA data by linking each regulatory action to its corresponding entry in the Federal Register (FR). This step is necessary to map the changes that final rules make to the Code of Federal Regulations (CFR) and to retrieve stakeholders' comments submitted on specific actions in the regulatory process.

Specifically, while the UA provides information on the CFR parts affected, it does not specify which sections are amended - sections are the lowest and most specific unit of organization in the CFR, as explained below. CFR parts associated with a RIN can include multiple sections, and regulatory actions may impact only a subset of those. Only by parsing the full text of the rule can we extract the specific sections affected by each regulatory action, and such data is available through the FR.

Additionally, although the UA includes a unique identifier for accessing comments data

[36]XML files were accessed at the following link: `https://www.reginfo.gov/public/do/eAgendaXmlReport`.

through Regulations.gov (i.e., the Docket # entry immediately below the timetable of actions in Figure A.2), it does not allow us to map comments to a single regulatory action. For instance, 8% of the regulatory processes for which we eventually retrieve comments from Regulations.gov solicited feedback on more than one proposed rule or notice of proposed rulemaking. Thanks to our extensive data collection, we are able to precisely map each comment to the specific regulatory action it pertains to. To achieve this, we need to first retrieve the unique identifier assigned by the FR to each action and then parse all comments submitted to each action through Regulations.gov.

Though seemingly simple, this exercise required extensive data collection, manual checks, and record linkage steps, often compensating for missing information and the lack of consistent use of unique identifiers through the four sources of data (Unified Agenda, Federal Register, Code of Federal Regulations, and Regulations.gov). In the following sections, we describe the information we retrieve from the FR and provide extensive information on our record linkage approach.

A2 Federal Register

The Federal Register (FR) serves as the official daily publication for rules, proposed rules, and notices of federal agencies. It contains regulatory documents having general applicability and legal effect. The FR is organized following a chronological format, with one volume for any given year and one issue for any given date. Each entry in the FR is assigned an FR document number and the same FR Cite used in the UA.

For our purposes, we rely on two types of information reported in the FR: a rich array of action-specific metadata and the text of the regulatory action (e.g., proposed or final rules). Similarly to the UA, the FR reports information on the publication and effective date of the action, the type of action (notices, proposed rules, final rules, corrections), and the parts of the CFR affected. Second, unlike the UA, the FR includes the full text of actions and a detailed description of the CFR parts and sections amended.

Extending the example from the previous section, the EPA regulatory process RIN 2050-AG83 includes two regulatory actions, each one with an FR document number. A.1 below reports the two RIN-FR Cite-FR Document number triplets.

Table A.1: Linking Unified Agenda and Federal Register.

RIN	FR Cite	FR Document Number	FR Type	FR Action
2050-AG83	81 FR 75781	2016-26381	Proposed Rule	Proposed Rule
2050-AG83	83 FR 5317	2018-02337	Rule	Final rule

Notes: The table reports the regulatory process ID (RIN), the citation of the regulatory action in the Federal Register (FR Cite), and unique identifier assigned to the action by the Federal Register (FR Document number) and the type of action the FR uses to describe the regulatory action (FR Type of action).

A3 Linking the Unified Agenda and the Federal Register

In this section, we describe how we link the Unified Agenda (UA) to the Federal Register (FR). The unit of observation in the UA is the RIN-FR cite. The unit of observation in the Federal Register is the FR document number. Our goal is to assign each of the 71,185 RIN-FR cite pairs from the UA an FR document number from the Federal Register. This allows us to link each regulatory action in the UA (e.g., proposed rule, final rule) to the corresponding text in the FR.

Three features of the data make this task particularly challenging.

1. **Multiple RINs can map into a single FR cite:** Since the FR cite is defined by a combination of the volume number of the Federal Register and the page (e.g., 81 FR 75781), multiple RINs can have the same FR cite if they are printed on the same page. This case occurs for 7.7% of the 64,357 unique FR cites in the UA.

2. **Multiple RINs can map into a single FR document number:** When multiple agencies jointly issue a rule, the UA reports a separate regulatory process for each agency, resulting in multiple RINs. The Federal Register, however, creates only one FR document number. This case occurs for 6% of FR document numbers that we eventually match to RINs.

3. **Missing RIN information:** Many entries in the Federal Register report an FR document number and an FR cite, but no corresponding RIN.

To overcome these challenges, we proceed in multiple steps:

Step 1: Matching via Federal Register API

- We use the Federal Register API to obtain, for each of the 34,414 unique RINs (from our 71,185 RIN-FR cite pairs), the associated FR document numbers.[37] We are able to retrieve at least one FR document number for 28,054 of the RINs (81.5%). We then query the API to obtain FR cites associated with each of the document numbers retrieved.

- This results in a RIN-FR cite-document number crosswalk covering 66% of the 71,185 RIN-FR cites in the UA.

The API was unable to return document numbers for all RINs. In Step 2, we verify whether the missing RINs (28.5%) are reported in the printed version of the Federal Register.

Step 2: Matching with Federal Register XML files

- We access XML bulk data from the printed edition of the Federal Register, and for each element (i.e., each document printed in the FR) we scrape information on the FR cite, FR document number, and – when available – the RIN.
- We then merge this data with the remaining, unmatched RIN-FR cites, keeping only unique matches. For cases that cannot be matched, we only match uniquely based on the FR cite. This allows us to improve the coverage for the crosswalk to 87% of the 71,185 RIN-FR cites in the UA.

In Step 2, we improved the coverage of the RIN-FR cites crosswalk by uniquely matching RIN-FR cites and FR cites to the XML data. 2,455 RIN-FR cites could not be matched in this step because the XML data listed multiple FR document numbers for the same RIN-FR cite. To make progress, we now disambiguate by using the title information provided in the UA and the FR.

Step 3: Matching based on title

- For each of the RIN-FR cite pair with multiple FR document numbers (Step 2), we retrieve the document title through the Federal Register API. We then match the UA title associated with an RIN to the document title from the FR.
  To allow for fuzzy matching, we use a deep learning model for record linkage to extract for each RIN-FR cite the FR document number whose title is most similar to the UA title (Arora and Dell, 2023). The model uses sentence transformers to convert titles to dense vectors and returns the title with the largest cosine similarity between the

[37] An example of the API call is the following: https://www.federalregister.gov/api/v1/documents.json?conditions%5Bregulation_id_number%5D=RIN

UA-title and every FR document-titles. A research assistant manually validated all the matches and removed false positives.

- Step 3 allows us to recover FR document number for 74% of the 2,455 RIN-FR cite pairs, increasing the coverage for the cross-walk to 89.5% of the 71,185 RIN-FR cites.

Step 4: Relaxing matching by allowing for typos

After Steps 1-3, 7,473 RIN-FR cite pairs remain without a corresponding FR document number. Extensive manual inspection revealed that this is often due to two frequent types of errors in reporting the FR cite.

1. The FR cite in the UA and the FR cite in the FR might have a 1-page difference. If documents are long, they are printed over multiple pages in the Federal Register, and the FR may report FR cite k and the UA FR cite $k \pm 1$.

2. A common data entry error, whereby the middle digit of the FR cite is shuffled (e.g., 1234 instead of 1324).

Informed by our manual checks, we thus relax our matching criterion to allow for $\pm$ 1 page difference in the FR cite as well as the middle digit shuffling. This allows us to recover 3,704 additional RIN-FR cite-FR document linkages. At the end of the Step 4, we are able to assign a FR document number to 95% of the 71,185 RIN-FR cites.

Step 5: Supplementary cases

Finally, 7,211 RINs report actions without a valid (i.e., a missing) FR cite. To rule out the possibility that these actions have a valid entry in the Federal Register that was simply not reported in the UA, we replicate Step 1 for each of the 7,211 RINs.

- For each RIN, we search through the Federal Register API and retrieve the associated FR document numbers. We then poll the API again to extract the FR cite for each of the FR document numbers.

We recover at least one FR document number for 9% of the 7,221 RINs, for a total of 1,437 RIN-FR cite-FR document tuples, which we add to the regulatory actions matched through Steps 1 to 4. Overall, these steps allow us to build a comprehensive crosswalk of 68,886 unique RIN-FR cite-FR document number observations, thus allowing us to link the vast majority of regulatory actions with their full text (from the Federal Register) and the comments submitted by stakeholders (from Regulations.gov) by using the common FR document number identifier.

A4 Code of Federal Regulations

The Code of Federal Regulation (CFR) is the stock of active and effective regulatory provisions. Specifically, the CFR "is the codification of the rules published in the Federal Register by the departments and agencies of the Federal Government."[38]

The CFR is divided into 50 titles that represent broad areas subject to federal regulation. Each title is divided into chapters, which usually bear the name of the issuing agency. Each chapter is further subdivided into parts that cover specific regulatory areas. All parts are organized into sections.

CFR titles are updated once each calendar year, on a staggered basis.[39] The annual update cycle is as follows:

- titles 1-16 are revised as of January 1
- titles 17-27 are revised as of April 1
- titles 28-41 are revised as of July 1
- titles 42-50 are revised as of October 1

The staggered update of titles is important information we leverage when determining the year when the changes made by a final rule are expected to be codified in the CFR. For example, a rule that is effective in March affecting Title 29 will be codified in the same year. Conversely, a rule published in the same month amending a section of Title 10 will be codified in the following year.

In the following section, we describe the steps we follow to extract the CFR sections final rules aim to revise. Table A.2 shows the CFR titles, parts, and sections affected by the final rule of the EPA regulatory process RIN 2050-AG83.

[38]Detailed description of the CFR is available through GovInfo, a government service that provides free public access to official publications from all three branches of the Federal Government, via the following link: `https://www.govinfo.gov/help/cfr#about`.

[39]Since 2017, an online version of the CFR has been updated on a daily basis. However, given the limited time coverage of the online version, our analyses rely on the yearly publications.

Table A.2: Linking Unified Agenda and Federal Register.

RIN	FR Cite	FR Document Number	CFR		
			Title	Part	Section
2050-AG83	83 FR 5317	2018-02337	40	241	2
2050-AG83	83 FR 5317	2018-02337	40	241	4

Notes: The table reports the regulatory process ID (RIN), the citation of the regulatory action in the Federal Register (FR Cite), and unique identifier assigned to the action by the Federal Register (FR Document number), and the sections of the CFR affected by the rule.

We download the yearly edition of the CFR directly from the GovInfo.gov portal.[40] Each yearly edition contains 50 XML files, one for each title. Each XML file is organized into multiple XML elements, one for each section.

A5 Detecting Rules' Changes to the Code of Federal Regulations

Final rules, when enacted, modify sections of the CFR. Recall the CFR is organized into titles, parts, and sections, and we need to extract the sections affected by the rule. While both the UA and the FR document-specific metadata report the CFR parts affected, only the text of the rule describes how the rule amends or revises each individual section.

To extract the title-part-sections affected by final rules, we perform four steps:

1. We collect the CFR title-parts affected by the rules and contained in the FR metadata.

2. From the yearly editions of the CFR, we compile a list of the universe of CFR title-part-sections codes ever published between 1997 to 2024, for a total of 609,591 unique title-part-section codes.

3. For every rule, we subset the list of section codes to keep only those contained in the CFR title-parts listed in the FR metadata of the rule, and we build a flexible regular expression that collapses all the possible title-part-sections (this allows us to flexibly extract even the most complicated section codes, e.g. 7.319.56-2d).

4. We extract each section mentioned in the text of the final rule (in the *List of Subject* section, where the rule describes regulatory changes).

Once we have a dataset at the FR document number (FRdn)-CFR title-part-section level (see Table A.2), we assign for each section the year when we expect to see the changes

[40] Bulk data can be accessed at `https://www.govinfo.gov/bulkdata/CFR`.

codified in the CFR. Because titles are updated yearly but on a staggered basis, the year of codification depends on the CFR title the rule amends and the effective date of the rule.[41]

We then take the text of each CFR title-part-sections published in any year between 1997-2024 that have been affected by the final rules in our sample and we extract the text as published in year t, after codification, and year $t-1$, prior to codification, in order to compare the two versions of the text. If a rule in year t introduces a new section, this will not have a text in $t-1$. Similarly, if a rule repeals a section from the CFR published in year $t-1$, the section will not have a text in year t.

From our crosswalk of RIN-FR cite-FRdn triplets, we have 33,049 unique documents that are classified as final rules in the Federal Register. For 98.9% of them, we can get information on the CFR title-part affected from the Federal Register API, and for 88.9% we successfully extract the affected CFR sections from the text of the rule. For 3,655 rules we are not able to extract any CFR section affected.

Continuing with our example from regulatory process 2050-AG83, our data shows that the final rule issued, FRdn 2018-02337, amends two sections of the CFR: title 40, part 241, sections 2 and 4. Now, consider the portion of the rule amending section 2. The text of the rule is displayed in Figure A.5. The rule adds three new definitions to CFR section 2.

Figure A.5: Text of rule from Federal Register.

PART 241—SOLID WASTES USED AS FUELS OR INGREDIENTS IN COMBUSTION UNITS

■ 1. The authority citation for part 241 continues to read as follows:

Authority: 42 U.S.C. 6903, 6912, 7429.

■ 2. Section 241.2 is amended by adding in alphabetical order the definitions "Copper naphthenate treated railroad ties", "Copper naphthenate-borate treated railroad ties", and "Creosote-borate treated railroad ties" to read as follows:

§ 241.2 Definitions.

* * * * *

Copper naphthenate treated railroad ties means railroad ties treated with copper naphthenate made from naphthenic acid and copper salt.

Copper naphthenate-borate treated railroad ties means railroad ties treated with copper naphthenate and borate, including borate made from disodium octaborate tetrahydrate.

* * * * *

Creosote-borate treated railroad ties means railroad ties treated with a wood preservative containing creosols and phenols and made from coal tar oil and borate, including borate made from disodium octaborate tetrahydrate.

* * * * *

[41] The effective date of the rule is often the same as the publication date. When we are not able to extract information on the rule's effective date, we use the publication date.

This rule became effective on February 7, 2018. Because titles 28-41 are updated as of July 1, the revisions of the rule are codified already in the 2018 edition of the CFR. We therefore compare the text of the section in 2017 (pre-codification) and in 2018 (post-codification). Figure A.6 shows the two versions of the section, respectively the 2017 (Panel A) and 2018 (Panel B) version.

Figure A.6: Text of CFR section before and after revision.

A) CFR 2017

§ 241.2

the environment considering the nature and toxicity of the non-hazardous secondary material.

Control means the power to direct the policies of the facility, whether by the ownership of stock, voting rights, or otherwise, except that contractors who operate facilities on behalf of a different person as defined in this section shall not be deemed to ''control'' such facilities.

Creosote treated railroad ties means railway support ties treated with a wood preservative containing creosols and phenols and made from coal tar oil.

Established tire collection program means a comprehensive collection system or contractual arrangement that ensures scrap tires are not discarded and are handled as valuable commodities through arrival at the combustion facility. This can include tires that were not abandoned and were received from the general public at collection program events.

B) CFR 2018

§ 241.2

the environment considering the nature and toxicity of the non-hazardous secondary material.

Control means the power to direct the policies of the facility, whether by the ownership of stock, voting rights, or otherwise, except that contractors who operate facilities on behalf of a different person as defined in this section shall not be deemed to ''control'' such facilities.

Copper naphthenate treated railroad ties means railroad ties treated with copper naphthenate made from naphthenic acid and copper salt.

Copper naphthenate-borate treated railroad ties means railroad ties treated with copper naphthenate and borate, including borate made from disodium octaborate tetrahydrate.

Creosote treated railroad ties means railway support ties treated with a wood preservative containing creosols and phenols and made from coal tar oil.

Creosote-borate treated railroad ties means railroad ties treated with a wood preservative containing creosols and phenols and made from coal tar oil and borate, including borate made from disodium octaborate tetrahydrate.

Established tire collection program means a comprehensive collection system or contractual arrangement that ensures scrap tires are not discarded and are handled as valuable commodities through arrival at the combustion facility. This can include tires that were not abandoned and were received from the general public at collection program events.

Notes: Panel A reports the text of CFR section 40.241.2 in the 2017 publication of the CFR. Panel B reports the same section in the 2018 version of the CFR. The red box highlights the three definitions that are added.

A6 Measuring Text Length and Readability

Once we have a pre-post codification version of the text for each title-part-section-year observation, we apply various measures of length and readability to both texts. We compute the number of characters, words, and sentences, as well as 46 different readability indexes. To compute such indexes we use the `quanteda` library in R (Benoit et al., 2018).[42]

[42] For a description of each index see Package documentation `quanteda.textstats` on CRAN, pp. 13-19, accessible at https://cran.r-project.org/web/packages/quanteda.textstats/quanteda.textstats.pdf.

In the analysis, we use two of the most popular indicators: Flesch's Reading Ease Score (Flesch, 1948) and the Flesch–Kincaid Grade Level (Thomas et al., 1975). The score is a numerical measure designed to evaluate the readability of English texts, indicating how easily a reader can understand a passage. The score is calculated using the average sentence length and the average number of syllables per word. Higher scores indicate simpler, more accessible text. The Flesch–Kincaid Grade Level is a readability metric designed to estimate the educational grade level necessary for a reader to understand a given text. It calculates a score based on the average number of words per sentence and the average number of syllables per word. The resulting score corresponds to a U.S. school grade level; for example, a score of 8.0 indicates that an eighth grader would typically be able to comprehend the text. These metrics are widely used in education, publishing, and content creation to tailor materials to specific audiences.[43] These indicators are now commonly used by government agencies and departments. The U.S. Army first used it for assessing the readability of technical manuals in 1978 and it is now a standard for the U.S. Department of Defense, the Internal Revenue Service and the Social Services Administration.[44]

To showcase how these scores are computed, let us consider USDA regulatory process RIN 0518-AA02, titled "Rules of Conduct at the United States National Arboretum". The USDA issued a final rule on September 23, 2005, with FRdn 05-18991. The rule amends 21 sections of CFR title 7, part 500. Due to its effective date, we compare the 2005 and 2006 editions of the CFR. Table A.3 shows the text of the section, the number of words, and the Flesch score before and after the adoption of the rule.

[43] Note that higher readability is associated with a higher Flesch score and a lower Flesch-Kincaid score. In the analysis, all scores are rescaled so that larger values are associated with greater readability.

[44] Source: https://medium.com/@annwylie/flesch-kincaid-grade-level-how-hard-is-it-ebb0bfcdfa87.

Table A.3: Example of CFR section before and after adoption of rule.

Section Text	**CFR Year**	**Nr. Words**	**Flesch Score**
Entering U.S. National Arboretum property or the operation of a motor vehicle thereon, by a person under the influence of intoxicating beverages or narcotic drug, or the consumption of such beverages or the use of such drug in or on U.S. National Arboretum property, is prohibited.	2005	52	29.4
(a) Entering USNA property or the operation of a motor vehicle thereon, by a person under the influence of intoxicating beverages or a narcotic drug, is prohibited. (b) Except as provided in subpart B of this part, possession of or consumption of intoxicating beverages on USNA property is prohibited. (c) The sale of alcoholic beverages on the grounds of the USNA is prohibited. (d) The possession of or use of narcotic drugs on the grounds of the USNA is prohibited.	2006	95	-26.6

Notes: Text of CFR section 7, title 7, part 500 before and after the section was revised by rule FRdn 05-18991. Columns 2 to 4 report the editions of the CFR, the number of words of the section, and the Flesch score (higher values signify easier readability - here values have been standardized to facilitate the analysis).

Not only does the section become longer but it also becomes more complex. Both texts require a college-level reading ability but the 2006 version is less readable because it contains a longer sentence and more instances of long words such as 'intoxicating', 'possession' etc.

A7 Comments Data

We access comments data through Regulations.gov, an online platform where individuals and organizations can submit comments to government regulations issued by federal agencies.

All executive departments and major independent agencies partner with Regulations.gov to solicit and publicize comments, although several smaller agencies and independent commissions are not partner agencies. While the time coverage of comments on Regulations.gov dates back to 2002, data by agency can vary depending on when the agency became a participating member.

For each one of the 68,886 RIN-FR cite pairs with an available FRdn, we extract all actions that are classified as proposed rules or notices of proposed rulemaking (NPRM) in the Federal Register. We remove all actions issued before 2003, when Regulations.gov was launched, for a total of 29,238 proposed rules. Since agencies started partnering with Regulations.gov at different times, we successfully retrieve information for 15,346 rules, 10,175 of which received at least one comment. We locate a total of more than 13 million comments submitted to the rules in our sample, with an average of 1,286 comments per proposed rule.

Most of the comments, especially those submitted by organizations, are uploaded as attachments in PDF, Microsoft Word, or plain text formats. We download a total of more than 2.8 million attachments and extract the text, performing, when necessary, optical character recognition.

The unit of observation in Regulations.gov is the docket ID-document level. A Docket is an electronic collection of documents related to rulemaking processes. The Docket may contain documents related to one or more Federal Register actions (e.g., proposed rules, notices, final rules), materials specifically referenced in those documents, and other documents relevant to the rulemaking process that the agency seeks to make accessible to the public.

We prompt the Regulations.gov API and download comments through five steps. First, for each FR document number, we retrieve a unique identifier assigned by Regulations.gov: the object ID. Second, for each object ID, we then extract the total number of comments. Third, for documents with a number of comments greater than 0, we extract all comments' unique identifiers. Fourth, we retrieve comment-specific metadata, including the author of the comment, the text of the comments, and the attachments to the comments.

To continue the example of EPA regulatory process 2050-AG83, in Table A.4 we report the object ID of the proposed rule identified with FR document number 2016-26381. This proposed rule received 4 comments, each with a comment ID and a title, as reported in the table.

Table A.4: Linking Federal Register and Comments Data.

FR Document Number	Regulations.gov		
	Object ID	Comment ID	Comment Title
2016-26381	09000064823626f9	0900006482448f6a	Comment submitted by Michael Schon, Vice President and Counsel for Government Affairs and Elizabeth Horner, Director and Assistant Counsel for Government Affairs, Portland Cement Association (PCA)
2016-26381	09000064823626f9	0900006482448466	Comment submitted by Jeffrey T. Miller, President and Executive Director, Treated Wood Council (TWC)
2016-26381	09000064823626f9	0900006482448370	Comment submitted by Seth L. Johnson, Attorney, Earthjustice
2016-26381	09000064823626f9	0900006482447693	Comment submitted by Robert D. Bessette, President, Council of Industrial Boiler Owners (CIBO)

Notes: The table reports the FR unique identifier (document number) assigned to the proposed rule from RIN 2050-AG83, and the respective object ID from Regulations.gov. The object ID returned four comments (with their unique identifiers), reported in the middle columns. The final columns reports the title of the comments.

When submitting a comment, users can type the text of their comments or they can attach a file including one or multiple comments. Downloading attachments is key to accessing relevant comments, for organizations and interest groups generally upload their comments as a PDF or MS Word file. For comments that are typed, we extract the text in machine-readable format directly through the Regulations.gov API. For comments uploaded as attachments, we download the attachment, and based on the format of the file, we apply several optical character recognition technologies to extract text from the file in a machine-readable format.

We classify the stance of the comments towards the proposed rules with state-of-the-art Natural Language Inference (NLI) techniques. An alternative, promising approach to stance detection that can effectively handle the complexities of varying linguistic contexts across different policy areas and agencies.

NLI leverages pre-trained language models that are designed for entailment classification tasks. A document *entails* a statement with some probability. For example, the statement "I fully support the EPA initiative." has a high probability of entailing "The author of this comment *supports* the proposed rule.” NLI operates by taking a premise (i.e., the comment) and a set of hypotheses (i.e., statements that are either true or false with some probability given the premise) and identifies the hypothesis with the highest probability of being true based on the comment’s text (Burnham, 2024).[45]

For example, our sample of comments includes one submitted by Seth K. Johnson, attorney at Earthjustice. Mr. Johnson submitted a 4-page-long file with the following opening statement:

> Earthjustice submits the following comments on the proposed rule in the above-named matter. For the reasons given below, EPA should not finalize the rule as proposed.

The full document represents the premise. The hypotheses are the three possible stances and the stance with the largest probability returned by the model is “Opposes” (p = .99).

We download and analyze a total of 12,785,789 comments.

88.9% of comments consist of only one document/text. When users submit a comment in machine-readable text along with one attachment, we consider the stance expressed in the attachment, as the text of the comment often simply states “See attachment.” (9.8% of comments). When users submit only two attachments, we keep the common stance if both attachments are assigned the same stance, or the stance with the largest predicted probability if the attachments have a different stance (only 31 comments). For the remaining comments having machine-readable text and 2 or more attachments (1.2% of comments), we keep the common stance if all documents have the same stance, whereas we keep the modal stance of the attachments otherwise.

57% of comments are classified as conveying a negative stance towards the proposed rule, whereas 38% have a positive stance. Among the proposed rules with the largest share of opposing comments, there is the Department of Education’s rule aimed at clarifying the “obligation of all schools [...] to provide an educational environment free from discrimination on the basis of sex, including through responding to incidents of sex discrimination.”, with 87% of opposing comments and a total number of comments equal to 238,948. Conversely, the rule proposed by the Department of Defense aimed at “amending the Federal Acquisition Regulation (FAR) to ensure that major Federal agency procurements minimize the risk of climate change” received significant support from interested parties, with 99% of the 34,977 comments analyzed supporting the proposed regulation.

[45] A simpler approach would be to perform some standard sentiment analysis on the entire text of the comment. However, research shows that stance (i.e., position or beliefs about an issue) is frequently uncorrelated with sentiment (Bestvater and Monroe, 2023).

B Predicting the Duration of the Rulemaking Process

In this section, we describe the procedure we implement to predict the duration of the rulemaking process. When comparing the duration of rulemaking processes assigned to teams of aligned or misaligned regulators, one key inferential challenge is that rules assigned to aligned regulators might take systematically shorter or longer to complete compared to rules assigned to misaligned ones. To mitigate this concern, we include the predicted duration of the rulemaking process in the battery of rule-specific covariates x_r'. Our approach follows the procedure proposed by Iaria et al. (2024), who compute the predicted number of citations of academic publications to examine gender gaps in citations.

We train a machine learning classifier on the text of the abstract of the rulemaking process to predict the latent duration of the process.

- First, we subset our sample of rulemaking processes to those with fully misaligned bureaucrats (13,056 out of 35,657 unique RINs). By restricting the training data to rulemaking processes assigned to misaligned bureaucrats alone, we purge the bias that stems from unobserved differences in the samples of rulemaking processes assigned to teams of aligned and misaligned regulators.

- Second, we apply standard text preprocessing steps to the text of the abstract: we remove stopwords and punctuation, we lowercase, and lemmatize each word.

- Third, to produce a matrix of predictors, we represent the set of abstracts as a matrix X of dimensions $R \times F$, where R is the number of abstracts and F is the total number of unique features, i.e. 1,2,3-grams (words). Each entry x_{rf} is a weighted frequency (*tf-idf*) of the n-gram in each abstract, which assigns greater weight to rare words.

- Fourth, we augment the matrix of predictors with a battery of rule-level covariates, agency, and year dummies.

- Fifth, to reduce the importance of outliers, we winsorize the training data to rules with duration up to the 99th percentile.

- Sixth, we train a Ridge regression model on 75% of the training data, regressing the logarithm of duration on the matrix of predictors, and we test the performance of the classification on the 25% of held-out test data. We find that the predicted duration explains 20% of the variance in the actual duration of rulemaking processes ($R^2 = 0.20$) in the test data.

- Finally, we train the same regression model on the total sample of rules written by misaligned bureaucrats (that we previously split into training and test data) and obtain a $R^2 = 0.33$. We use the model to compute the predicted duration for the total sample of 35,657 rulemaking processes.